An enquiry into the Chinese housing market; evidence from spatial analysis and real options

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Declaration

Whilst registered as a candidate for the above degree, I have not been regisitered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submitted for any other acamedic award.

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Contents

List of Figures

List of Tables

Abstract

This thesis investigates the modelling of house prices in China. The first empirical chapter (Chapter 4) scrutinises the determinants of property prices in seven districts of Beijing, China. While the house prices of the panel model, noted in recent literature (Huang et al., 2017), are confirmed in the case of flat-related factors. Chapter 4 also reveals several new flat-related factors, such as directions of house facing (orientation) and house floor level, influencing house prices that have not been presented in previous studies (e.g., Hyuna and Milchevab, 2018 and Yang et al., 2019). However, as well as these flat-related factors, this investigation also incorporates macroeconomic factors, such as GDP, inflation, income, unemployment rates, mortgage rates and factors of fiscal policy. The application of panel analysis extends the current literature by taking into account endogeneity in the GMM framework with instrumental variables.

The second empirical chapter (Chapter 5) investigates the spatial statistics of house prices in Beijing. This chapter examines whether house prices in one region are affected by house prices in neighbouring regions. This investigation also analyses how house prices in one region are affected by unknown characteristics of the neighbouring regions. It explores whether the explanatory factors of house prices in one region are affected by explanatory factors of house prices in neighbouring regions. In addition, this chapter investigates the spill-over effects of explanatory factors on house prices. This investigation also examines the partitioning of direct effect and indirect effect from the impacts of the neighbouring factors on house prices. Chapter 5 overcomes the shortcomings of the previous studies ((Mussa et al., 2017) by extending the range of examining spatial models, providing reasonable spatial model selection procedures, and employing improved spatial weights to analyse spill-over effects of explanatory factors.

Finally, the thesis investigates real options with the spatial analysis in the Chinese real estate markets (Chapter 6). This investigation extends the real options method with the spatial Durbin model (SDM), making this the first study in which real option forecast have been assessed in a spatial case. This method improves the accuracy of predicting house prices by considering neighbouring house prices. Chapter 6 measures the degree of price uncertainty by a generalised autoregressive conditional heteroskedasticity (GARCH) model. The Black-Scholes' (1973) pricing model is employed to explore the option premium of land value. Evidence is found in this chapter provides there are real options in China's real estate markets. Uncertainty about future house prices of neighbouring regions drives up land prices in China. The results suggest that uncertainty about future house prices in neighbouring regions decreases investment activity in the current period; and uncertainty about future house prices in neighbouring regions increases land prices. Market house prices in neighbouring regions reflect a premium for optimal development. The likelihood of developing the land is lower in terms of the increase of one-standard-deviation.

Chapter 1 Introduction

The purpose of this thesis is to explain the factors influencing the housing market in China from 2000 to 2015, including house characteristics, regional identities and economic fundamentals and how they impact on house price, geographic variation in house price and profits of housing investments.

The thesis main objectives are provided in three folds. First to provide a quantitative analysis on house pricing, in particular to examine how house attributes, regional economic condition and regional identities affect house price, taking into account geographical interrelations, between 2002 and 2014 in Beijing, China. Second to extend current literature by investigating and formulating new factors that affect house prices in terms of demand and supply for housing, in the context of advanced spatial panel analysis techniques and real options methodology in Beijing and China from 2000 to 2015. Third to examine and extend real option methodology, by developing models that examine the mechanisms and compute the factors that affect real option premium in the above mentioned, integrated, context.

The rest of this chapter is organised as follows. Section 1.1 reviews the background, highlights the research problems, hence, the need and motivation of this thesis. Section 1.2 presents the main research questions. Methodologies implemented is presented in Section 1.3. Section 1.4 summarises the findings and contributions of each chapter. Then, Section 1.5 concludes by the overall structure of the thesis.

1.1 Research Background and Motivation

The housing market has been involved in a significant transformation on real estate model over the past forty years in China. China's house prices were increasing rapidly from ¥503 in 1988 to ¥6,793 in 2015. The house prices of Tier 1 cities (i.e. Beijing, Shanghai, Shenzhen and Guangzhou) were continually rising, even though after the implementing of housing policies[1] (e.g. implements regulations of housing construction and house structures), and monetary policies[2] (e.g. controlled banks with real estate development loans, land loans, loan payments and personal housing loans), which proposing to curb the irrational increasing

[1] See housing policies ("217th policy" in 2001, "8th policy" in 2004 and "6th policy" in 2006) in Chapter 2.2.1.
[2] See monetary policies ("121st policy" in 2003, "18th policy" in 2004, "Notice on Strengthening Commercial Real Estate Credit Management" in 2007 and "10th policy" in 2010) in Chapter 2.1.1.

house prices. Accordingly, the sustaining increase of house prices in China, especially in Tier 1 cities, provide the opportunities for the real estate investors with irrational speculation. While the rapidly increasing house prices may raise a number of concerns on the unbalanced relationship between the demand for houses and that of supply and the risk of the implication of housing bubbles (Black et al., 2006; Chang et al., 2008; Cheng et al., 2014; Himmelberg et al., 2005; Hui and Yue, 2006; Smith and Smith, 2006).

There are concerns that the transformation of the Chinese real estate model has increased motivation for rapid increasing house prices in China, especially in Tier 1 cities since 1998 (Gan et al. 2010). The housing privatisation stimulates the household's housing consumption and then increases equilibrium housing demand in China (Wang, 2011). Regarding the diversifications from housing allocation system, the Chinese citizens were required to purchase housing on the market at the family. This situation unleashed a flood of private housing demand and prompted a significant increase in the cost of commodity residential housing in China (Chen et al., 2012). The house attribute can be regarded as the house characteristics, which has the implicit value (Rosen, 1974). It is evident that house characteristics importance of house price has attracted attention from researchers (Bajari et al., 2012; Jim and Chen, 2009; Malpezzi, 2002; Rosen, 1974; Wong et al., 2005). Rosen (1974), who factor consumer behaviour into a hedonic regression, establishes the relationship between the product's price and its attributes.[3] In practice, the regression coefficients are generally regarded as implicit or "hedonic" prices (Bajari et al., 2010). The implicit price can be described as the additional value of a product when individual attributes are increased while all other attributes remain fixed. For instance, in China's land market, the land with water facility is more expensive than that of without water facility, when the other attributes remain the same, such as size and other facilities. This is because the land with water facility has a particular attribute, which is the additional value of this land. Rosen (1974) established the hedonic regression to provide the house price based on utility-maximising behaviour. The estimate of implicit prices proposes that the consumer's willingness to pay for a small alteration in a particular attribute is marginal. Moreover, "these implicit prices can be used to recover marginal willingness to pay functions for use in valuing larger changes in attributes" (Bajari et al., 2010).

[3] For studies investigating hedonic regressions, see, for instance, Rosen (1974); Bajari et al. (2012); Carrillo et al. (2014).

As previously discussed above, the house characteristics have to be provided as much detailed as possible in order to accurately estimate the implicit values of the house. However, it is uncertain whether there are ‘omitted variables’ leading to biased estimates of the implicit prices. When applied to real data, several ‘omitted house characteristics variables’ seem to be significant in the theoretical models. Jim and Chen (2009) suggested that daylight and views from houses are significant factors affecting house prices. The previous studies ignore the condition of the room, which also can be the endogenous variables of house prices. This investigation tests these endogenous variables through the numbers of rooms with orientations, including room conditions that proxy daylight and natural ventilation in order to contribute the previous studies in term of introducing new flat-related factors that affect house prices.

Collectively, given the fixed-hold attributes of houses, the house price is variationally in terms of the external influences such as the supply of housing. Review the housing policies from China’s government, which attempts to regulate housing construction and house structures to adjust the supply of house and indirectly restrict the rapid increasing house price. The market response to these policies was negative for Beijing. Therefore, it is crucial to figure out the reasons why these policies are ineffective.

House had been regarded as a primary source of investment for individuals in China, which allows the investors to achieve potential profit with speculative and alternative incomes. In 2017, housing sales achieved 13.37 trillion RMB accounting for 16.4% of China’s GDP (Liu and Xiong, 2018). This situation provides maximum stimulation to encourage investors to make a decision on their own deal. An individual property transaction is dominated by what the investor believes will happen to the market in the future without regard to any possible distortions (Cheng et al., 2014). Regarding the theory of ‘distortions beliefs’, the investors ignored the risk of low demand, referred to income, may have fostered the financial circumstances that enabled property prices to rise alongside credit expansion, and subsequently spark the crisis (Gennaioli et al., 2013). Though the theory of ‘distortions beliefs’ illustrates the irrational increase of China’s house prices, another reason of irrational increase of house prices can be also attributed to Naylor (1967), who illustrates that the fiscal policy influences the housing demand indirectly. The increasing tax rates reduce the aggregate demand for GDP; subsequently, the changes in aggregate demand for GDP will indirectly influence housing demand by the diversities of intermediate economic factors, such as income, employment and prices (Naylor, 1967). In other words, the endogenous variables for housing demand influence house prices directly. Naylor (1967) also provides that an increase of investment in fixed assets will lead to a rise in GDP so that increase the prices of goods.

To date, there is a substantial literature on the influencing economic factors to house prices in China and foreign countries, for instance, income (Capozza et al., 2004; Chen and Patel, 1998; Hui and Gu, 2009; Milne, 1991; Riddel, 2011; Shen and Liu, 2004, Zhang and Yi, 2017), mortgage payments (Kohn and Bryant, 2010; Lee, 1997; Li and Chand, 2013; Mints, 2007, 2008; Yu, 2010), inflation (Gan et al., 2012; Horioka and Wan, 2007; Irving, 1911), fiscal policy (Feltenstein and Farhadian, 1987; Naylor, 1967; Taylor, 2000), housing starts (Maisel, 1963). Regarding the rapid development of economy in China, it is suggested that the accurate measurement of house prices is essential to monitor economic fundamentals (Hui and Gu, 2009; Li et al., 2018; Li and Chand, 2013; Shen and Liu, 2004; Yu, 2010) and investment behaviour (Huang and Yin, 2015; Wong et al., 2005; Zhang and Yi, 2017). While the endogenous variables of housing demand are not mentioned in the previous studies. The method of defining the housing demand is not unique. In this investigation, the housing demand is identified by housing starts multiple floor level of the house. The housing starts is a potential standard which decides the final housing demand in terms of 'a theory of fluctuation in residential construction starts' (Maisel, 1963). Whereas the housing starts is the size of building permission, the investigation improved the housing demand factor in terms of relating to floor level, which makes housing demand into underlying units. Findings of this investigation suggests there is an inverse U-shape relationship between housing demand and house prices, which is consistent with the theory of 'conventional wisdom' (Galbraith, 1958). This research also tests the endogenous economic fundamentals for house price in order to explore the economic variables influencing house price indirectly. This research regards the housing demand and mortgage payment rates as endogenous variables referred to the previous studies and China's government monetary policies. To do this, the previous model is improved by taken account into instrumental variables.

There is a possible reason for the rapid increasing house price in Tier 1 of China which is spill-over effects. Chow et al. (2016) investigate house price convergence in 34 Chinese cities. They apply convergence model with contemporaneous spatial dependence in house prices and find that price convergence and positive spatial spill-over are both present. The spill-over narrows the gaps between the growth paths of house prices in neighbouring cities. Zhang et al. (2015) examine the house price spill-over effect with capital cities of Yangtze River Delta

Economic Zone in China. Shanghai, Hangzhou, Nanjing, Hefei's house prices index is tested over the period 2001-2014. They find the house price spill-overs in the Yangtze River Delta Economic Zone because of high market integration, but the direction and speed of spill-over are different. The spill-over effects are also the essential influencing factors for the foreign countries. Holly et al. (2011) find that the dynamic spill-over affects house prices in the neighbouring areas. Van Dijk et al. (2011) examined two groups of regions in the Netherlands and found that house prices within the same group had the same dynamics across time, while the dynamics were different across different groups. The spatial heterogeneity which exists is based on the different demand and supply of house price across clusters (Dieleman et al., 2000). Abate (2017) indicated a rising spatial correlation in house prices and income in the USA during the period in question. The evidence indicate that house price has geographical variation. The house price could be influenced by interactions with the neighbouring regions. The changes in population and information asymmetries cause the ripple effects of house prices (Pijnenburg, 2017). The increasing demand that occurs as a result of migration to regions where house prices are comparably low results in an increase in house prices. The spatial dependence is caused by information asymmetries suggested that new information referred to the housing market in one area is transported gradually to other submarkets (Meen, 1999). Wood (2003) provided that spatial heterogeneity is caused based on the speed of responses of national economic shocks in one region, where the housing market is more liquid and where new information affects house prices more rapidly than in the neighbouring regions. Meen (1999) argues that heterogeneity arises because of variations in household behaviours and household compositions. While the Chinese housing market is significantly different from the other countries' housing market in terms of the development levels. Thus, the spatial autoregressive and spatial error component are essential to be investigated in understanding the spatial spill-overs of house prices in China.

Burgess (1925) argued that 'the ideal construction of the tendencies of any town or city to expand radially from its central business district (CBD), which is encircling the downtown area'. A third area is dwellings for the workers in industries who desire to live within easy access of their work with good house conditions. 'Residential area' of high-class apartment buildings is constructed belonging to this zone. However, Alonso (1964) considers that the increasing population and old residential property limited the implementation of this theory in the real world. Hoyt (1939) provided that 'the pattern of residential location could be explained in terms of sectors'. As the population increased, there is enough space to live in this area. However, the people worked in CBD represent the highest income group. There are no houses above them abandoned by another group. These customers must build new houses on vacant land in the other area, which causes the movement of the high-rent area. Richardson (1971) describes a trade-off theory, which 'assumes household find its optimal location relative to the centre of the city by trading off travel costs'. This theory denotes that through increasing the distance from city centre, the rent of houses or the house costs would be declined. The household through maximising the utility of house location balances the costs of the house and satisfies more space for living (Richardson, 1971).

The evidence has increased motivation for investigating the spatial analysis of house prices in Tier 1 cities of China. Because Tier 1 cities have more CBDs which have the higher house prices than that of surroundings based on Burgess (1925). The interactions of house price in CBD and surroundings will encourage the continued increases in house prices. However, the previous studies did not provide the degree of second-order or higher-order neighbouring effects. This investigation finds that house prices in one district and the surrounding districts exist the significance of spatial autocorrelation in Beijing. The results reveal strong house price spill-overs when the increase in house price, size of building started, average wage, income, tax, and a population of the neighbouring regions is taken into account. This investigation overcomes the previous studies in terms of providing the partitioning spill-over effects on house prices based on the regional information asymmetries. In the findings, the significance of the partitioned spill-over effects on urban population and GDP are in the second-order surrounding regions. This result is consistent with and contributed to the 'sector theory' (Hoyt, 1939), which the differences in household income cause the changes of residential location and house prices. Thus, it is valuable information for the regulators of real estate market. Because the appropriate distribution of submarket of CBD reduces the degree of income differences, so that decreases the geographical house price variation.

Reviewed the previous policies and studies (Pindyck, 1991; Razak et al., 2018), which are analysing the past events in the housing market, the future performance of housing market and the forecasting profits for the investors motivated this thesis to explore. According to classical economic theory, it is recommended to make an investment when the net present value is positive. However, the previous scholars (McDonald and Siegel, 1986; Titman, 1985) proposed in their theoretical work, that if the future is unclear and investments cannot be reversed, the ability to change to alternative investments at a future date has economic value. This is referred to as a "real option". According to Myers (1977), real options are the right for the investor to buy or sell a physical asset after they have purchased that asset. In the same way that a financial option allows a person to purchase a security at a predetermined price at some point in the future, real options permit future investment, dependent on new information. This suggests that real options should increase the value of assets and slow down or postpone investment. It is recommended to estimate the use of real options in the real estate market. The land on which a house or other property is built is valued as an option, while the underlying or primary asset is the building itself. There is considerable evidence, as well as developments in modified models, to support the application of real options in evaluating real estate markets (Chiang et al., 2006; Grovenstein et al., 2011; Tsekrekos and Kanoutos, 2013; Razak et al., 2018).

Whether the application of real options is appropriate for China's real estate market has been suggested by the previous studies (Huang and Rong, 2017; Hui and Fung, 2009; Li et al., 2014; Shi et al., 2015; Tang and Wang, 2017; Wang et al., 2016; Zeng and Zhang, 2011).The uncertainties of various control policies, most of which are administrative and quite volatile, are always affecting China's real estate market between 2005 and 2011; and found a one-standard-deviation increase in the volatility of M2 change rate and interest rate lowers the likelihood of land development by 13.39 % and 16.51 % (Wang et al., 2016). The incomplete information is a real estate market characteristic in China's real estate market, and it influences the development of land in the urban city from 2002 to 2010 (Tang and Wang, 2017). The factors influencing the public rental housing fraud are analysed in the real estate market in China (Zeng et al., 2017). The uncertainty of apartments' physical attributes, firms' financial position and other economic conditions influencing apartment price is analysed by Shi et al. (2015). The uncertainty of the real estate market in China should be explained in an appropriate method based on China's real estate market characteristics. However, the previous studies on real options of real estate markets focused on the uncertainty of future house prices are applied by OLS estimator, which does not consider the effects of neighbouring regional influences (Cunningham, 2006; Quigg, 1993; Titman, 1985). This investigation overcomes the previous studies in terms of the methodology implemented. In this research, the effects of price uncertainty on neighbouring regions are considered by the spatial model. The method of this investigation employs to accomplish this is the spatial Durbin model, making this the first time that real option forecast has been tested in a spatial context. Spatial analysis improves the accuracy of predicting the value of house prices and considers the surrounding regions' house prices and their effects on the house prices of a particular region (Muss et al., 2017). The SDM model includes spatial fixed measures, time fixed measures, and spatial and time fixed measures of anticipated future prices and price uncertainty. This approach provides a basis for testing the main expectations of real options with regard to land development: namely, that neighbouring house price uncertainty should delay building activities and increase the value of vacant land. This context appropriately solves the agency problem based on investment timing (Jensen and Meckling, 1976). When the shareholder and agents capture the information of surroundings at the same time and plan the investment of options, the information asymmetric and timing of investment are solved in order to establish an optimal capital structure and maximise the shareholder's value.

1.2 Research Questions

The main purpose of the first empirical chapter is to evaluate the determinants of property price with house characteristics and economic fundamentals in seven districts of Beijing, China between 2002 and 2014. This investigation has three main objectives. First to provide a quantitative analysis of house transactions to examine whether the house characteristics and economic fundamentals influence the house prices significantly. Second to investigate whether there are 'omitted variables' that lead to biased estimates of the implicit house prices. Third to explore whether endogenous economic fundamentals and house characteristics variables are leading to biased estimates of house prices. In doing so, this chapter overcomes the omitted variables of house characteristics, leading to biased estimates of the implicit house price, compared with the previous studies (Rosen, 1974; Bajari et al., 2010). The endogenous economic fundamentals, which are leading to incorrect biased estimates of coefficients and result in an inefficient model, are tested, based on the 'quantity theory of money' (Irving, 1911), the theory of 'conventional wisdom' (Galbraith, 1958), 'a theory of fluctuation in residential construction starts' (Maisel, 1963), and consumer behaviour on house price (Rosen, 1974).

This second empirical chapter investigates the spatial statistics of house prices in Beijing from 2003 to 2013. It examines whether house prices in one region are affected by house prices in neighbouring regions. It also analyses how house prices in one region are affected by unknown characteristics of the neighbouring regions. Research exploring the spatial analysis of house prices can be divided into two areas. First, the spatial autoregressive model can assess the value of houses. Second, the regression approaches with geographical weights can analyse the spatial heterogeneity. When examining regional data with house price, the two specific spatial aspects need to be considered, namely spatial dependence and spatial heterogeneity (Anselin, 1988).[4] The transportation of the house prices across space is the spatial dependence, and the difference of house prices in the dynamics is called spatial heterogeneity (Pijnenburg, 2017).[5] Chapter 5 considers this spatial dependence is referring to the information asymmetries which cause the spatial spill-overs of house prices. It explores whether the explanatory factors of house prices in one region are affected by explanatory factors of house prices in neighbouring regions. In addition, this chapter investigates the spill-over effects of explanatory factors on house prices. This investigation evaluates this not only by different regional economic factors but also with respect to the intensity of spill-overs in order to assess the range of spill-overs, which examines the partitioning of direct effect and indirect effect from the impacts of the neighbouring factors on house prices. This research aims to overcome the shortcomings of the previous studies by extending the range of examining spatial models, providing reasonable spatial model selection procedures, and employing improved spatial weights to analyse spill-over effects of explanatory factors.

This third empirical chapter investigates real options with the spatial analysis in China's real estate markets. This investigation extends the real options method with the Spatial Durbin Model (SDM), making this the first study in which real option forecast have been assessed in a spatial case. In contrast, Chapter 6 does not rely on micro-data but instead employs new detailed macro-level datasets for 31 provinces in China between 2000 and 2015. This is because of the determinants of house prices, such as neighbouring house price effects and neighbouring unobserved characteristics. Previous studies on real options of real estate markets focused on the uncertainty of future house prices are applied by OLS estimator, which does not consider the effects of neighbouring regional influences (Cunningham, 2006; Quigg, 1993; Titman, 1985). Chapter 6 considers the underlying asset of land as well as neighbouring house prices, neighbouring unobserved characteristics and economic conditions. This investigation evaluates this by real options in a spatial manner, which improves the accuracy of predicting the value of house prices and considers the neighbouring regions house prices. It measures the degree of price uncertainty by a generalised autoregressive conditional heteroskedasticity (GARCH) model. The Black-Scholes' (1973) pricing model is employed to explore the option premium of land value. This chapter investigates whether the

[4] For studies investigating spatial analysis, see, for instance, Anselin (1988); Anselin et al. (2003); Anselin et al. (2008).
[5] See Pijnenburg (2017) for spatial analysis of US house prices.

uncertainty about future house prices in neighbouring regions influence investment activity in the current period. It also examines whether the uncertainty about future house prices in neighbouring regions influence land prices. This research explores whether the market house prices in neighbouring regions reflect a premium for optimal development in terms of the likelihood of developing the land.

1.3 Research Methodologies

This thesis deals with numerous topics in the field of real estate markets. The investigation undertakes within this thesis a wide variety of econometric methodologies, such as the optimal method of determinants influencing house prices, the need to capture house price spill-overs, and the uncertainty of house price on real options.

The literature with regard to analysing the determinants of house prices has employed a wide range of statistical estimators and tests. The estimator is illustrated by OLS regression technique as implemented by (Cameron and Trivedi, 2009). The Breusch-Pagan test is employed to explore the existence of homoscedasticity or heteroscedasticity in the OLS estimator. The Breusch-Godfrey LM test explores whether there are conditionally uncorrelated observations or not. This investigation also applies panel data regression with fixed effects and random effects. Panel data analysis is conducted by taking account of group effects and time effects. Based on the implementation of the Hausman Test, the appropriate model (i.e. fixed effects or random effects) are selected. The Wooldridge test is applied to test the conditionally uncorrelated observations in the panel models. The heteroscedasticity test (likelihood-ratio test) is implemented in terms of testing the conditional homoscedasticity in the panel models. The Friedman test aims to explore the cross-sectional correlation. Given the nature of this research, least squares estimation methods generate biased and inconsistent estimates (Baltagi, 2001). To address this concern, this investigation implements the generalised method of moments (GMM) method, which accounts for endogeneity by using alternative independent variables that are suspected to suffer from endogeneity. Baltagi (2001) argued that employing the values of the other variable regressors as instruments can increase consistency and efficiency of the model. The IV-GMM method restricts unobserved heterogeneity and limited the consistency of the dependent variable. The Hausman tests are applicated to explore the presence of endogenous variables. The Sargan test of the instrumental variables is implemented to illustrate whether the instrumental variables are relative to the error of regression. The first-stage test of GMM aims to test whether the instrumental variables are relative to endogenous variables. These econometric techniques are appropriate to achieve the investigation of the determinants of house prices.

The second empirical chapter investigates the spatial statistics of house prices in Beijing. To address this, the research incorporates various methodologies to capture house price spill-overs. The creating of the spatial matrix is applicated in terms of the identifying the neighbours of regions with specific contiguity. The spatial autocorrelation tests are implemented with Global Moran's I in order to confirm the spatial dependence. Through the Lagrange Multiplier diagnostics (LM tests) and robust LM tests, the type of spatial dependence (i.e. spatial error or spatial lag) is explored. Regarding the type of spatial dependence, the appropriate spatial model is recognised, including spatial autoregressive model (SAR), spatial Durbin model (SDM), spatial autoregressive model with autoregressive disturbances (SAC) and spatial error model (SEM).[6] In the panel models, Hausman test, Breusch-Godfrey LM test, Breusch-Pagan test are implemented, which is similar to the investigation of the determinants of house prices. This investigation applies Wooldridge LM test and Breusch-Pagan test in the spatial model in order to explore the presence the autocorrelation and homoscedasticity respectively. Moreover, this research implements the partitioning spill-over effects techniques, which is advanced in the area of spatial analysis. LeSage and Pace (2010) provide that the empirical results of spatial models are analysed by direct effects, indirect (spill-over) effects and total effects in the further research. The reason is due to "the change in a single observation (region) associated with any given explanatory variable will affect the region itself (a direct impact) and potentially affect all other regions indirectly". This chapter also applies the statistic of the likelihood ratio test the best fit models for testing spill-over effects (Klugman, Panjer and Willmot, 2012).

The final empirical chapter investigates real options with the spatial analysis in China's real estate markets. The Black-Scholes' (1973) pricing model is employed to explore the option premium of land value. The spatial Durbin model (SDM) is implemented in terms of forecasting the future house prices in this area, comprehensively the neighbouring information and the neighbouring house prices, which improved the accuracy of forecasted house prices. This investigation measures the degree of price uncertainty by a generalised autoregressive conditional heteroskedasticity (GARCH) model. The future price uncertainty

[6] See Figure 3.3 for process of choosing spatial models.

suggests that developers' confidence in their predicted price forecast depends on the availability of forecast prices in the recent past (Cunningham, 2006). Combining the GARCH model and real options approaches, the investigation employs variance of GARCH model as house price volatility in the real options approaches.

1.4 Summary of Findings and Contributions

This thesis deals with numerous topics in the field of real estate markets. It addresses various models of house prices to analyse issues such as the optimal method of determinants influencing house prices, the need to capture house price spill-overs, and the uncertainty of house price on real options. Following is a detailed description of each chapter.

1.4.1 Findings and Contributions of Chapter 4

Chpater 4 evaluates the determinants of property price with house characteristics and economic fundamentals in seven districts of Beijing, China between 2002 and 2014. The findings confirm that economic factors have influenced the property price based on the economic theories (Cheng et al., 2014; Maisel, 1963). The mortgage down payment rates influence house prices negatively and significantly referring to economic fundamentals which is in line with Yu (2010) and Li and Chand (2013). This result implies that the policy of mortgage down payments is efficient to restrain the rapid growth of house prices. When the housing market investors persistent in buying houses, ignoring the high degree of mortgage payment rates, the demand for houses contains at a high level encouraging the house price to increase in terms of the speculation. When the supply exceeds the demands, the house prices remain high level would cause housing bubbles; which is consistent with finding of Cheng et al. (2014) in terms of 'distortions beliefs'. The findings also provide that the increasing average income rise property prices. This finding is in line with Hui and Gu (2009) and Shen and Liu (2004). It implies there is a higher possibility of housing bubbles with more speculative investors, who have more salaries. This investigation finds there is an inverse U-shape relationship between housing demand (housing starts*floor level) and house prices. This is similar to Li et al. (2018), which means the higher housing starts, the higher demand on houses so that increases the house prices in Beijing. However, this investigation suggests house price increases when the demand is lower than supply, and the excess supply of houses decreases the prices. This shows consistent finding with Maisel (1963) in terms of 'a theory of fluctuation in residential construction starts'. The property characteristics have influenced the property price significantly, which indicates that consumer behaviour is an essential aspect of housing market (Rosen, 1979). Home size influences house price positively, which is in line with Fang et al. (2016) in terms of costs of China's characterised consumer behaviour of households. It implies that the larger home size in China increases the demand for housing. The higher floor level of houses, the higher prices. Whereas, in a tall building, the increasing prices from the lower floor level to the middle floor level; from the middle floor level to the upper floor level, the floor level influences house prices negatively. This result is similar to a previous study (Wong et al., 2005), which suggests the higher demand for middle floors. The number of bedrooms has a significant negative influence on property prices, which result is consistent with the find of Fahey (2016) in terms of privacy. The houses facing north and south is significant and positive for the prices. This is because houses facing north and south have better natural ventilation and more daylight, which improves the natural quality of a house and its energy efficiency. This result is never found in previous studies (Bajari et al., 2010; Huang and Yin, 2015; Rosen, 1974; Zhang and Yi, 2017).

In terms of the endogenous effects on house price, the central bank interest rates, money supply, local government revenue, local government expenditure and total investment in fixed assets indirectly influence house price negatively, when the factor of mortgage payment rates is an endogenous variable. This is not in line with Taylor (2000) and Galbraith (1958). In the 'conventional wisdom' (Galbraith, 1958) the decreasing spends of government decrease the aggregate demand for GDP; subsequently, the decline of aggregate demand for GDP will decrease the price of goods. This may be because of China's rapid economic growth. As the good condition of economic growth, the decreasing government spends cannot restrain the demand for investments in the housing market. The investment in fixed assets and the local government general budgetary revenue affects housing demand negatively and significantly, which is in line with the finding of Naylor (1967) and Galbraith (1958). This result implicates that the house price could be decreased through restrain investments and increase government revenue indirectly because investments and government revenue influence the demand for houses in Beijing. The investigation also finds that the more bedrooms that are facing southeast and southwest or that are facing southwest and northwest with higher floor level, the higher house price. The more living rooms that are facing west or east with higher floor level, the higher house price. This is because the house facing south and west have more extended daylight, which increases the temperature of the room, so that increase the electrical efficiency. However, the bedrooms facing southwest, southeast or northwest not only keeps daylight but also reduces west sunburn and improves natural ventilation to improve sleeping context. The living room improves west sunburn increasing the whole house temperature so that increase house efficiency. Moreover, the higher floor level of houses, the more efficient daylight and natural ventilation. These results are in line with Zhang and Yi (2017), who find the house characteristics influences the house prices in Beijing. Thus, this investigation finds the more numbers of rooms with proper orientation, the better condition of the room is which has good daylight and better natural ventilation. These results implicate that the government illustrate the policies about relating house structure is efficient.

This chapter overcomes the previous studies in terms of the introduction of new flat-related variables. Compared with the previous studies (Bajari et al., 2010; Huang and Yin, 2015; Rosen, 1974; Zhang and Yi, 2017), the flat-related factors, such as directions of house facing (orientation) and square of floor level, FR^2, are never found. Without these factors, the implicit house price could be biased estimated. The essential finding of these new flat-related factors provides there is an inverse U-shape relationship between floor level and house prices. This investigation illustrated house orientation influences the condition of the bedroom and the condition of living room significantly and indirectly affects the house price in IV-GMM analyses, which improved the theoretical standpoint to understand the relationship between house characteristics and house prices.

In addition to the above, previous economic research has considered the variable of house demand that was designed primarily to determine the house prices. Based on the economic theory of supply and demand, excessive demand encourages the investor to have more confidence in investing in the property so that this increases the house prices (Rosenthal et al., 1991). Previous studies have found that the income elasticity of demand for housing is well below one (Carrillo et al., 2014; Glaeser et al., 2008; Hoyt and Rosenthal, 1990; Rosen, 1974; Rosenthal et al., 1991). In contrast, the present investigation applies housing starts multiple by floor level, $HPP * FR$, as property demand. This is because to housing starts is a potential standard which decides the final housing demand (Maisel, 1963) in terms of 'a theory of fluctuation in residential construction starts'. Moreover, this investigation employed the IV-GMM model to test the endogeneity of housing supply for the property prices respected to the instrumental variables with investment in fixed assets and local governments general budgetary revenue. This approach provides the determination of supply for houses be flexible with the economic conditions.

In an attempt to fill the gaps from previous studies, this investigation extends previous research in terms of the data sample. This investigation examines an extended period (2002-2014), which provides a sample with the advantage of 17,143 transacted property records with detailed information, from the Beijing core real estate area. This chapter linked transacted property records with property addresses to track the regional effects.

The application of panel analysis (i.e. fixed effects and random effects) extends the current literature by taking into account endogeneity in the IV-GMM framework with instrumental variables. In this regard, this investigation conceptually resembles Bajari et al. (2012), who investigate property prices the role of air pollution with hedonic regression. Empirical testing of the aforementioned issues provides a valuable tool for regulators in the Beijing area, because, to the best of our knowledge, it is the first study of its kind that examines all the above; it can also be useful for regulators in other industries, such as banking and insurance. In this chapter, the assessment and remediation of house price will depend on the understanding of their influencing factors.

1.4.2 Findings and Contributions of Chapter 5

Chpater 5 finds that house prices in one district and the surrounding districts exists the significance of spatial autocorrelation. The results reveal strong house price spill-overs when the increase in house price, size of building started, average wage, income, tax, and a population of the neighbouring regions is taken into account. The evidence for the disposition effect is based on the below results.

The house price spill-overs in Beijing area exist when there is an increase in the population of the neighbouring regions, significant upper house price spill-overs are detected in terms of increasing house prices in the neighbouring regions. This result is similar to Zhang et al. (2015) and Chow et al. (2016), which means the urban population influence house prices positively and significantly in Beijing. This finding is in line with Alonso (1964), who provides the population is a significant factor in the economic analysis, because the population changes the demand for the number of houses. In the theory of ‘the concentric zone’ (Burgess, 1925), the development of ideal construction of the city expands from its

CBD. The workers live near CBD aims to easy access to their work. Thus, the demand for house surrounding CBD is high, which causes the increase in house price. The findings of this analysis are also in line with Burgess's theory (1925) that the distance from district to CBD influenced the house price significantly and negatively. This encourages the regulators of Beijing housing market to establish the rational distribution of fixed assets effectively deter the unstable house price variation referred to the population changes.

The differences in household income cause changes in residential location and house prices based on the 'sector theory' (Hoyt, 1939). This result is in line with Shen and Liu (2004). The income significantly influences the house price in Beijing and changes the distribution of house prices. This investigation provides a similar result to Hoyt's theory (1939), which the average wage of employees in the real estate market leads to an increase in house price. This finding is also in line with the theory of 'the concentric zone' (Burgess, 1925), which presents the high-income group 'who have escaped from the area of deterioration' changes the demand of residential location. This encourages the regulators of Beijing housing market to establish the subsidiary CBD in Beijing in order to arrange rational distribution of fixed assets.

Evans (1973) found that there is an equilibrium relationship between the density and revenue of houses in 'the theory of the supply of space'. Thus, even though there is enough space for construction, the irrational density of buildings leads to lower revenues of the house. Size of building starts, which instead of the supply of houses, influences house prices positively. This result is in line with Hanink et al. (2012) and Zhang et al. (2018) who provide house starts is a potential determination of new construction rate which reflects the supply of housing market in Beijing. However, the result is not very significant. The result is similar to Evans (1973), who suggests a rational space and density of constructions are significant to households. Thus, it encourages the regulators of Beijing housing market to control the building permits and continue updating the policy of construction so that rationally monitor the supply of houses.

The research found the taxes and other charges on principal business of enterprises for real estate development lead to an increase in house price significantly. This result is similar to the previous studies (Li and Chand, 2013; Liu, 2013), which means the taxes and other charges on principal business of enterprises for real estate development influence house prices negatively and significantly in Beijing. Based on the trade-off theory (Evans, 1973), the maximum utility of the household is the objective of the choice of location. The increasing tax added the costs of construction, and then the developers will increase the house selling price so that balance the costs. When the household considers the house price, they will change the location of living so that the patterns of residential location changes. Thus, it encourages the regulators of Beijing housing market to control the tax rates, so that have a rational distribution of constructions.

The results of partitioning analyses are appropriately explaining the effects of surroundings, which can approach the utilities. Because of loss aversion, homeowners who intend to sell their properties will not lower their asking price, even when they see house prices declining in neighbouring regions. Loss aversion reduces the number of transactions in the housing market and, reduces the amount of house price spill-over. Results of this study are similar to previous findings (Genesove and Mayer, 2001; Engelhardt, 2003; Anenberg, 2011) with regards to loss aversion in the housing market. This result is also in line with the Yang et al. (2015), who show that the results of significant levels of the partitioned indirect effects in the second order are higher than those of the other order neighbours, which are referred to in the complicated estimation process in spatial Durbin dodel. Thus, it is suggested that the regulators of Beijing housing market should monitor the economic factors and population in the different order regions in order to adjust the house prices.

The evidence is found for spatial dependence of house prices: house prices in one region are influenced by the house prices in neighbouring regions, positively and significantly in Beijing. The evidence is found for spatial heterogeneity of house prices across space: house price spill-over is greater in neighbouring regions when neighbouring house prices are increasing than when neighbouring house prices are declining. The evidence is found for spatial spill-over effects of explanatory factors: increases of the average wage, income, tax, urban population and house price of last year increase the house price positively in neighbouring regions; a decrease of unemployment drives down the house prices in neighbouring regions. These factors have spill-over effects across space.

From the theoretical standpoint, these findings are likely to contribute to the theory of “the concentric zone’ Burgess (1925) that the information will expand radially from its central place or the city leading to information asymmetries in the surroundings. Consistent with this view, the findings reveal that the house prices in Beijing have a geographical variation and expand radially from CBD. This encourages the city planner of Beijing to simulate the regulation of the United States, which predicts the future pattern of land use in order to decide the optimal distribution of fixed assets investments. The rational distribution of fixed assets effectively averse the unstable house price variation referred to the information asymmetries.

This investigation is the first study to provide the partitioning spill-over effects on house prices based on the regional information asymmetries. In the findings, the significance of the partitioned spill-over effects on urban population and GDP are in the second-order surrounding regions. This result is consistent with and contributed to the ‘sector theory’ (Hoyt, 1939), which the differences in household income cause the changes of residential location and house prices. Thus, it is valuable information for the regulators of real estate market. Because the appropriate distribution of submarket of CBD reduces the degree of income differences, so that decreases the geographical house price variation.

This chapter extends previous research in terms of the data sample and independent variables used, and by combining methods used in economics and geography. In particular, this investigation examines 15 regions of Beijing over an extended period (2002-2014). It contains detailed information, building on and extending the work of Bhattacharjee et al. (2016), who analysed spatial heterogeneity and endogenous spatial dependence in Portugal. Regional house price records are linked with the coordinates of regions to track the spatial heterogeneity of house prices, and the region-related factors are employed in Beijing. Most of the previous empirical studies that combined geographic factors focused on the area of environment, health outcome, crimes and policy analyses (Gelfand, 2014; Hund et al., 2015; Neelon and; Seliske et al., 2016; Terán-Hernández et al., 2016). These factors can be extended by our method with spatial partitioning, which can analyse the intensity of spill-over effects of explanatory factors.

1.4.3 Findings and Contributions of Chapter 6

Chapter 6 investigates real options with the spatial analysis in China’s real estate markets. The findings suggest that it is more appropriate to employ a spatial model rather than a non-spatial model in forecasting the underlying assets based on the Lagrange Multiplier (LM) tests. The results illustrate that neighbouring house prices affected house prices in this region, supporting the idea that house price has a ripple effect (Pijnenburg, 2017). Similar empirical results were obtained by Farlow (2004), who found that house prices were higher in cities with increased income and lower CPI and unemployment rates. In the spatial Durbin model (SDM) analysis of underlying house price, this study found an increase in income equivalent of 1% is associated with a 41.2% rise in house prices. This result is in line with Tang and Wang (2017), who suggest income increases the house price in China. Moreover, the unemployment rate and CPI is negatively correlated with house prices. Similar empirical results were obtained by Harris et al. (2013) and Farlow (2004), who found that house prices were higher in cities with increased income and lower CPI and unemployment rates in China. On the other hand, the spatial fixed model is the first time applied in the following analysis (real options). Thus, there is no previous studies' results. The results of implied volatility analysis provide that house price in China has ARCH effects. This result is in line with Wang et al. (2016), who found ARCH effects for house prices in Hangzhou housing market, China. It is also similar to the study of Cunningham (2006), who found ARCH effects for house prices in Seattle. Based on the results, the standard deviation of residential housing market in China ranges from 2.14% to 23.49%, depending on the time series of house prices. This result is in line with Wang et al. (2016), who provide a one-standard-deviation residential housing market in Hangzhou ranges from 13.39 % and 16.51 %. Referred to the results of uncertainty and timing of land development, it is found that uncertainty delayed land development, as the coefficient of uncertainty was negative (-1.101). This result is in line with Tang and Wang (2017), who suggest the rising housing demand is accompanied by developers' strategic delay of land development in China. It provides the uncertainty of future information delay the land development in China based on land flexibility. The results also provide the similar results to Wang et al. (2016), who found the uncertainty delay the land development by 42% in Hangzhou, China. Based on the analyses, the results provide that the uncertainty affected land value by 1.82% significantly and positively. The unemployment rate influences the land value by 40.2%, significantly and negatively. These results are in line with Tang and Wang (2017) and Shi et al. (2015), who suggest the uncertainty increases the land value.

Market prices indicate a premium for optimal development of land, which according to our estimates has a mean of 16.28% of the land value. A one-standard-deviation increase in uncertainty reduces the likelihood of development by 1.101%. These results differ from those of previous studies. Wang et al. (2016) found the real-option premium 9.76% in housing market in Hangzhou, China. Yao and Pretorius (2004) found the real-option premium 11.75%

in housing market in Hongkong, China. Quigg (1993) found a real-option premium of 6% on undeveloped land that is relative to the deterministic price. Cunningham (2006) posited a one-standard-deviation increase in the vacant land price of 1.6% in Seattle. This research also estimates that standard deviation of real estate asset values in China ranges from 2.14% to 23.49%, which relies on the time series of property prices. Wang et al. (2016) provide a one-standard-deviation residential housing market ranges from 13.39 % and 16.51 % in Hangzhou, China.

This context appropriately solves the agency problem based on investment timing (Jensen and Meckling, 1976). When the shareholder and agents capture the information of surroundings at the same time and plan the investment of options, the information asymmetric and timing of investment are solved in order to establish an optimal capital structure and maximise the shareholder's value. Regarding the evaluation of land price, the increasing one-standard-deviation in price uncertainty raises the land price. If there is a greater level of price uncertainty according to the economic information, then the vacant land will be traded at a premium above discounted future rents in current low capital use.

The results of this study suggest that investors in China's real estate do take note of real options, even in sectors such as new home construction that is highly competitive and economically important. That real options are present in land markets is further evidence for the need to include real options in capital investment models. Real options have wider implications concerning the importance of price stability and the need for consistent government policy to stimulate fixed investment.

Most research in this area has focused on the house price uncertainty in a panel dataset. This approach provides a basis for testing the main expectations of real options with regard to land development: namely, that neighbouring house price uncertainty should delay building activities and increase the value of vacant land. This investigation extends the real options method with the spatial Durbin model (SDM), making this the first study in which real option forecast have been assessed in a spatial case. The evidence of this research links spatial analysis and GARCH analysis, which adds to the overall understanding of house price uncertainty. This investigation overcomes the prior studies by extended sample with three datasets have been assembled for this investigation: house price files, land price files and GIS files for each location. When they are combined, these records produce a data set of 496 average house prices and average land prices in 31 provinces of China, for the period 2000 to 2015.

Rather than extracting expectations from subsequently reported advantages, this investigation uses the Black-Scholes' (1973) pricing model to explore the option premium of land value, which concerns current stock price, time until option exercise, option striking price, risk-free interest rates and standard deviation. For the conception of real options, the analyses considered market land value as current stock price, future house price as option striking price, and house price volatility as standard deviation (Quigg, 1993) in order to determine the land option premium.

1.5 Overall Structure of the Thesis

The thesis is organised by one chapter of literature review, one chapter of the Chinese housing market background, three empirical investigations and one chapter of conclusion. Detailed structure is as follows:

Chapter 2 critically reviews the previous studies related to spatial analysis and real options in the housing market.

Chapter 3 presents the development of the Chinese housing market from 1978 to 2015.

Chapter 4 introduces the first empirical investigation "An Empirical Analysis of the Effect of Housing Characteristics on Property Price in Beijing". This chapter is structured by the introduction, theoretical framework, the hypotheses, methodology and data, empirical findings and conclusion.

Chapter 5 presents the second empirical investigation "The Spatial Analysis and Spill-Over Effects of House Price in Beijing". This chapter is structured by the introduction, theoretical framework, the hypotheses, methodology and data, empirical findings and conclusion.

Chapter 6 discusses the third empirical investigation "The uncertainty of house prices and real options in China". This chapter is structured by the introduction, theoretical framework, the hypotheses, the model, robustness of findings and conclusion.

Chapter 7 reviews the empirical chapter. It summarises the main findings of three empirical investigations and general conclusion for the thesis. It also offers a further path in this line of research.

Chapter 2 Literature Review

2.1 Introduction

The objectives of this chapter are to examine the spatial effects on Chinese house prices and to motivate the models of real options that will be employed in this thesis. Section 2.2 reviews the spatial characteristics of house prices in China. In particularly, Section 2.3 highlights the spatial econometrics in house prices with univariate models (Section 2.3.1) and multivariate models (Section 2.3.2) of spatial effects on house prices. Section 2.4 includes a summary review of spatial econometrics in house prices and a general discussion about the gaps existing in the current literature. Section 2.5 reviews the characteristics of real options in the real estate market. In principally, Section 2.6 highlights the real options approach applied to the real estate market. Section 2.7 reviews the real options approach applied to other sectors of economy based on the classifications of real options. Section 2.8 includes a conclusion of real options applied to the real estate market and a general discussion about the gaps between various methodologies.

2.2 Spatial Characteristics of House Prices

Several studies found that house prices are characterised by spatial correlations, meaning that prices in one area are affected by prices or unknown characteristics in nearby areas (Holly et al., 2011; Pijnenburg, 2017). To examine the spatial correlations, we must define, methodologically, what are the neighbouring areas. To imposes a data structure through neighbouring areas we use spatial weight matrix methodology based on two major approaches. First, by modelling the spatial correlations as a distance-based approach, such as inverse distance, fixed distance and K nearest neighbours. Second, by using contiguity-based spatial weight matrices, mainly based on polygon or lattice data (Cliff and Ord, 1973). In this study, we use contiguity-based methods, because they limit the dimensions of the spatial matrices, and spatial correlations of house prices become non-stochastic, making spatial weight matrix more easily applicable. Contiguity-based methods are employed in this study also due to the different city sizes of polygons in China territory. The contiguity-based spatial weight matrix as given by the following equation:

$$W = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \tag{2.1}$$

where n provides the number of observations for the whole regions. i and j represent the region i and region j. W_{ij} is an element in the spatial weight matrix, representing the spatial weight between region i and region j.

Previous studies suggest that Chinese house prices have spatial effects in terms of spatial dependence (Chow et al., 2016; Yang et al., 2017).[7] The spatial dependence is characterised as prices are dependent on prices or unknown characteristics in neighbouring regions. In other words, the house prices are spatially correlated with prices or errors in nearby regions (Anselin et al., 2008). In this circumstance, spatial dependence can be detected through the robust Lagrange Multiplier lag or error test (Elhorst, 2010). By modelling the spatial dependence, not only house prices contain neighbourhood relations but also spatial lag model (SAR) or spatial error model (SEM) is applicable. A stationary house pricing model includes price spatial dependency with a form of spatial lag dependence (Equation 2.2) or spatial error dependence (Equation 2.4) as given by the following equation:

$$P = \rho WP + \beta X + \varepsilon \tag{2.2}$$

where P is a $N \times 1$ vector of house price. ρ is a spatial correlation parameter. W is a $N \times N$ spatial weight matrix. β provides the $K \times 1$ vector of regression coefficients. X represents an $K \times 1$ vector of explanatory variables. ε is a $N \times 1$ vector of error. N and K are the number of observations.

$$P = \beta X + \nu \tag{2.3}$$

$$\nu = \lambda W \nu + \varepsilon \tag{2.4}$$

where P is a $N \times 1$ vector of house price. β provides the $K \times 1$ vector of regression coefficients. X represents an $K \times 1$ vector of explanatory variables. ν is assumed to be a $N \times 1$ vector of independent and identically distributed errors. W is a $N \times N$ spatial weight matrix. λ is spatial autoregressive coefficient.

Extensive studies illustrate that Chinese house prices in space exhibit spatial effects in terms of spatial heterogeneity (Wen and Tao, 2015; Yang et al., 2018; Zhang et al., 2017).[8] Spatial heterogeneity implies the structural instability or non-stationarity of parameters or determinants across space and is present in alternative forms which can be split into two

[7] Generally, spatial dependence is the spatial relationship of variable values or locations (Anselin, 2002).

[8] Spatial heterogeneity is a property generally ascribed to a landscape or to a population referred to the uneven distribution of various concentrations of each species within an area. For instance, regarding spatial heterogeneity of burglary risk, if all geographic areas in a study region have the same risk of burglary then we say that the risk is homogeneous. If there are areas with significantly higher risk than others (e.g. urban areas may have a higher risk of burglary than rural areas) then such a map displays heterogeneity (of risk).

categories. First, if the house prices in nearby areas are affected in a different way by the same factors, spatial heterogeneity is present in terms of spatially varying coefficients. Second, the circumstance, that house prices are characterised by different distributions (e.g., with a different mean or variance) for distinct regions, which is known as spatial regimes, occurs spatial heterogeneity in terms of structural differences across space (Anselin, 2017). Accordingly, spatial heterogeneity illustrates that the effects of spatial dependence or determinants on prices are different from that of in nearby regions (Anselin et al., 2008). Spatial heterogeneity is present in the form of non-constant error variances (heteroscedasticity) or the variable regression coefficients in the regression model based on Chow test (Baltagi, 2013, pp. 319-320; Chow, 1960). By incorporating the spatial heterogeneity, house prices become stationary structure across space and spatial fixed effect model is applicable, which is expressed as:

$$P = (\iota_T \otimes \alpha) + \beta X + \varepsilon \tag{2.5}$$

where P is a $N \times 1$ vector of house price. α is a $N \times 1$ vector of individual fixed effects, with the constraint that $\alpha' \iota_N = 0$ and stacked by T times, and, as before, $E[\varepsilon\varepsilon'] = \sigma_\varepsilon^2 \iota_{NT}$. β provides the $K \times 1$ vector of regression coefficients. X represents an $K \times 1$ vector of explanatory variables. ε is a $N \times 1$ vector of error.

In order to successfully model house prices in space it is essential that the spatial characteristics of the data are examined by the various models under consideration. Modelling empirical spatial effects of house prices such as spatial dependence spill-overs and spatial heterogeneity spill-overs are mentioned in previous studies (Hyuna and Milchevab, 2018; Meen, 1999; Wang et al., 2017). Contributory to such modelling has been the Maron's I model, spatial autoregressive model (SAR), spatial error model (SEM), spatial autoregressive model with autoregressive disturbances (SAC) and spatial Durbin model (SDM). There are numerous applications of these models to modelling economic data including estimating and forecasting house prices spill-overs in terms of spatial dependence and heterogeneity (Brady, 2014; Costello et al., 2011; Fereidouni et al., 2016; Holly et al., 2011; Hyuna and Milcheva, 2018; Teye and Ahelegbey, 2017). However, there is no unanimous method that the most appropriate modelling approach deals with the spatial dependence and heterogeneity on house prices in the Chinese housing market (Chow et al., 2016; Zhang et al., 2015; Zhang et al., 2017). A conventional approach a researcher has to employ is to examine various models and evaluate them, both in-sample and out-of-sample.

In remainder of this chapter, several conditional spatial dependence and heterogeneity models and partitioning technique are presented.

2.3 Spatial Econometrics in House Prices

Referred to the theoretical and empirical literature (see in Section 2.3), various models are appropriate to examine spatial effects on house prices, and several models are employed in real options. These models are divided into univariate and multivariate frameworks. The univariate models focus on the form of spatial pattern (e.g., clustering or dispersed or random) in mapped house prices due to geographical proximity. The multivariate models deal with the specified spatial autoregressive models based on the rejection of the null hypothesis (e.g., spatial lag or spatial error) and demonstrate the spatial partitioning technique with the spill-over effects on price determinants.

2.3.1 Univariate Models of Spatial Effects on House Prices

Several studies have documented the spatial autocorrelation characteristics of house prices which can be generated by spatial dependence and heterogeneity (Wang and Gao, 2014; Zhang et al., 2015).[9] According to these studies, spatial autocorrelation is present in house prices which represents prices are likely to be similar to that of nearby areas. This assumption is known as the first law of geography which defines “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970). Accordingly, it implies that the spatial observations, such as house price, are improbable to be independent statistically (Doh and Hahn, 2008). Such a phenomenon can be detected by Moran’s I statistical test which provides the presence or absence of spatial autocorrelation.

Global Moran’s I model determines the existence of the spatial autocorrelation in the model residuals. Global Moran’s I model aims to measure the average level of spatial autocorrelation, which can be written as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{W \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{2.6}$$

$$W = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \tag{2.7}$$

[9] Spatial autocorrelation assesses the variable correlation which is relative to this variable’s spatial location. It approaches the variable features and the spatial attributes for the locations (LeSage, 2010).

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2.8}$$

where x_i represents the attribute value in region i. n provides the number of observations for the whole regions. i and j represent the region i and region j. $\bar{x}$ is the mean value of variable x. W_{ij} is an element in the spatial weight matrix, representing the spatial weight between region i and region j. The row standardised spatial weights matrix is provided in equation 2.8. The null hypothesis of Moran's I model represents that the absence of spatial autocorrelation of observations in the spatial pattern (e.g., distuibution of observation is random, $I = 0$). Positive spatial autocorrelation is present when high or low values tend to cluster in space ($0 < I < 1$). Negative spatial autocorrelation denotes the values of observation are dispersed ($-1 < I < 0$) and considers the spatial heterogeneity.

Several limitations restrict the application of Global Moran's I model for the examination of spatial autocorrelation. Moran's I model determines the absence or presence of spatial autocorrelation but not specified what form or process (Ismail, 2006). Global Moran's I model provides a misleading result when the spatial structure of a process varies from one area to another because it measures the average level of spatial autocorrelation across the obtained insights (Lloyd, 2007). Global Moran's I model has limited the approaches to the specified attribute value of that region and cannot represent the situation in the attribute value of it (Fotheringham et al., 2000). Accordingly, the purpose of spatial heterogeneity test has transferred from identifying and interpreting global regularities to characteristics across space and local privileges (Fotheringham et al., 2000).

Local Moran's I model emphasises the heterogeneity of spatial data and the direction to show spatial non-stationarity (Goodchild, 2009). In contrast with the global model which measures of the average level of spatial autocorrelation, local model runs a circular window over the obtained insight and computes the value of the statistic in each window based on the characteristics (Boot and Okabe, 2007). One simple method to associate the geographical information at the local level is to specify regional dummy variable or regional interaction terms as spatial components in regression. The value of Local Moran's I model equation is written as:

$$I = \sum_i \frac{I_i}{N} \tag{2.9}$$

$$I_i = \frac{X_i}{m}\sum_j W_{ij}X_j \tag{2.10}$$

$$m = \frac{\sum_i X_i^2}{N} \tag{2.11}$$

Lloyd (2007) illustrates that the application of the local models is more complex than the global model which factors of the size of a circular window or type of transformation influence the result values. Therefore, Local Moran's I model provides geographical problems to the discrete nature of approaches (Clark, 2007). Anselin et al. (2013) argues that geographically weighted regression approaches for exploring local spatial autocorrelation are appropriate to deal with discrete nature. Geographically weighted regression clarifies the distinct nature in terms of incorporating the modelling variation in spatial relations between multiple variables.

Index Moran' I is generally employed in spatial econometrics to test the similarity or dissimilarity (positive correlation, negative correlation) of house prices in spatial analysis (Helbich et al., 2014). This is because house prices have spatial autocorrelation in space (Baumont, 2004). For instance, Yang et al. (2017) employing eight group metrics data from 31 provinces in China between 1998 and 2011, suggest that a Moran' I model is needed to capture the spatial autocorrelation in house prices. They find that Moran's I index is significant and positive which represents house prices in Chinese provinces are not randomly distributed in space but clustered. Wang and Gao (2014) employs two cross-section data from 2005 to 2012 in Beijing and find that the null hypothesis of no spatial autocorrelation in house prices is rejected. In the USA, Cohen (2016) using a panel dataset of annual house prices from 363 Metropolitan Statistical Areas between 1975 and 2013, provides that Moran' I model is applicable to test whether house prices spatial effects are more pronounced following the crisis. In this thesis, the Moran' I model will be one of the competing models, although we look forward to including specified spatial autoregressive models which reject the null hypothesis (e.g., spatial lag or spatial error).

2.3.2 Multivariate Models of Spatial Effects on House Prices

Our multivariate framework is three-fold. First, the models focus on the spatial dependence of house price based on the rejection of the null hypothesis (e.g., spatial lag or spatial error). Second, the models address the spatial heterogeneity of house price and its determinants. Third, the models deal with the spatial partitioning technique with the spill-over effects on price determinants. These models are discussed in sections 2.3.2.1, 2.3.2.2 and 2.3.3.3, respectively. The spatial partitioning models differ from the other two in terms of the transformation of spatial weight matrices. Spatial partitioning models employ higher orders of neighbourhood effects of prices and determinants as spatial correlation intensity rather than unique neighbourhood effects from first order neighbours. For further discussion, see below.

2.3.2.1 Models to Examine Spatial Dependence of House Prices

A large number of empirical evidence documents that house prices have spatial effects in terms of spatial dependence (see Chow et al., 2016, among others). The stationary spatial models exhibit the spatial dependence of prices depending on the formal structure of hypotheses in omitted spatially lagged dependent variable (SAR) or error variance (SEM). In the former test (Lagrange Multiplier spatial lag or error test), the null hypotheses for spatial dependence are specified as:

$H_0: \rho = 0, \quad H_a: \rho \neq 0$ (SAR in Equation 2.2 for spatial lag dependence)

$H_0: \lambda = 0, \quad H_a: \lambda \neq 0$ (SEM in Equation 2.4 for spatial error dependence)

Through obtaining spatial dependence, house prices contain neighbourhood relations in space and then the spatial correlation is not present in the SAR or SEM. It implies house prices have spatial effects in terms of spatial dependence. Therefore, the distinguish of spatial dependence is a starting point.

Spatial econometrics considered spatial effects involves the spatial autoregressive modelling which are the spatial lag model (SAR), the spatial error model (SEM), and the joined approach accommodating both spatial lag and spatial lag operations (SAC). These spatial econometric models establish assumptions for the formation of spatial correlation in the sample depending on where the autoregressive process is to present (Kissling and Carl, 2008). The general spatial autoregressive model with spatial autoregressive errors is given by:

$$P_{it} = \alpha + \tau P_{it-1} + \rho \sum_{j=1}^{N} W_{ij} P_{jt} + \beta_k \sum_{k=1}^{k} X_{itk} + \nu_{it} \tag{2.12}$$

$$\nu_{it} = \lambda \sum_{j=1}^{N} W_{ij} \nu_{it} + \varepsilon_{it} \tag{2.13}$$

where P_{it} is a $N \times 1$ vector containing one observation of the dependent variable for each spatial element ($i = 1, \dots, N$). N is the number of regions. t represents the observation at time t. P_{it-1} is the value of dependent variable for last year. ρ provides the parameters of spatial lag. λ illustrates the parameters of spatial error. X_{it} represents the vector of explanatory variables. The vector X_{it} consists of a $N \times K$ matrix. K is the number of explanatory variables. β provides the coefficient of K explanatory variable. W is a $N \times N$ spatial weight matrix.

The spatial autoregressive model assumes that the autoregressive process occurs in the response variable. In SAR, λ is equal to zero and ρ is unequal to zero (Equation 2.12 and 2.13). In SEM, it is assumed that spatial dependence is present in the error term, where ρ is equal to zero and λ is unequal to zero (Equation 2.12) and the error terms, υ_{it} , are independent and identically distributed (Equation 2.13). Nevertheless, in the spatial autoregressive model with autoregressive disturbances (SAC), λ and ρ are both unequal to zero, which assumes spatial dependence is present in both the error term and the response variable.

The neglect of spatial effects on OLS regression leads to the unbiased results but inefficient parameter estimators and biased variance estimators (Anselin, 2014). Regarding this circumstance, estimated parameters are in the incorrect confidence intervals leading to incorrect predicted house prices (Basu and Thibodeau, 1998). The frequent development in publication involving spatial effects has been perceived after the 1990s (Alselin et al., 2004) although spatial autocorrelation has been analysed for a period of time (Cliff and Ord, 1970).

Spatial autoregressive models (e.g., SAR, SEM and SAC), in general terms, seems to be appropriate in terms of examining effects of house prices and unknown characteristics on neighbouring regions and explaining spatial characteristics of house prices such as spatial dependence (Mussa et al., 2017).

The empirical applications of the spatial autoregressive models in house prices are plentiful. Baltagi et al. (2014) examine the annual house price variation from across 353 local authority districts in England 2000 to 2007 and finds spatial lag term (in SAR) is present on house prices implying a positive correlation between house price locally and that in neighbouring districts. DeSilva et al. (2012) examine the effects of Blacks and Hispanics on house prices in the U.S. and find the influences of Blacks in a neighbourhood is smaller in spatial methods (SEM and SAR) than that employing simple OLS and Hispanics have no significant influences on house prices by spatial methods. The advance of the spatial autoregressive model, in the field of house prices, compared to the OLS model derives from the consideration of spatial dependence being able to examine the dependencies in the higher-order spatial dimension.

The spatial dependence on house prices is also known as spill-over effects in the housing market (Pijnenburg, 2017). The empirical evidence for spatial spill-overs of house prices is the UK housing market, which provides the spatial and temporal diffusion of shocks are dominant for London and propagated contemporaneously and spatially to other regions in the UK (Holly et al., 2011). Across the U.S. states, the spatial diffusion regarding impulse response functions is statistically significant for approximately three to four years due to the increase of house prices over a period from 1975 to 2011 (Brady, 2014). Cohen et al. (2016) investigates spatial effects in house price dynamics with 363 Metropolitan Statistical Areas data across the US from 1996 to 2013 and finds the growth rates of urban house prices show the spatial diffusion patterns. Teye and Ahelegbey (2017) illustrate that the temporal dependence and house price diffusion patterns are present from distinct provincial housing sub-markets in the Netherlands. In Australian, the capital city house prices forecasts can be improved by employing house prices from neighbouring cities 1984Q3 to 2008Q2 (Costello et al., 2011). In South Korea, the spatial dependence of house prices is more significant in a rising housing market than in a falling market in Seoul between 2006 and 2015 (Hyuna and Milcheva, 2018). Fereidouni et al. (2016) examine house price diffusion among Malaysia's major economic regions (Kuala Lumpur, Selangor, Pulau Pinang and Johor) and between each of these regions and neighbouring Singapore from 2000Q1 to 2011Q1. They find the ripple effect of house prices is present among Malaysia's major economic regions.

For China, empirical evidence regarding spatial spill-overs of house prices is substantial, which examine the capital cities of Yangtze River Delta Economic Zone (e.g., Shanghai, Hangzhou, Nanjing and Hefei) from 2001 to 2014 and find the house prices spill-overs are due to the high market integration but the direction of spill-over are different (Zhang et al., 2015). Chow et al. (2016) provide that both house price convergence and positive spatial spill-over are present in 34 Chinese cities. The house prices spill-overs narrow the gaps between the growth paths of house prices in one region and that of neighbouring cities. Zhang et al. (2017) investigate the ripple effect of house prices between 35 metropolitans by spatial location and regional economic level in China from 2006 to 2012 and find the house prices diffusion path is present between economic regions. The spill-over effects of the housing market in China are significantly different from that of other countries in terms of the different city sizes of polygons and the varying development states of cites across the country. In this thesis, the spatial autoregressive and spatial error component are essential to be examined in understanding the spatial spill-overs of house prices in China.

The extension of the spatial autoregressive model is spatial Durbin model (LeSage and Pace, 2009). Spatial Durbin model (SDM) is a generalisation of SAR or SEM model which also includes spatial correlation of explanatory variables, and is written as:

$$P_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} P_{jt} + \beta_k \sum_{k=1}^{k} X_{itk} + \theta_k \sum_{k=1}^{k} \sum_{j=1}^{N} W_{ij} X_{jtk} + \upsilon_{it} \tag{2.14}$$

$$\nu_{it} = \lambda \sum_{j=1}^{N} W_{ij} \nu_{it} + \varepsilon_{it} \tag{2.15}$$

where P_{it} is a $N \times 1$ vector containing one observation of the dependent variable for each spatial element ($i = 1, \dots, N$). N is the number of regions. t represents the observation at time t. ρ provides the parameters of spatial lag. λ illustrates the parameters of spatial error. X_{it} represents the vector of explanatory variables. The vector X_{it} consists of a $N \times K$ matrix. K is the number of explanatory variables. β provides the coefficient of K explanatory variable. θ_k represents the parameters of spatial lag of explanatory variables. W is a $N \times N$ spatial weight matrix.

The spatial Durbin model (SDM) investigates more spatial interactions rather than the spatial hedonic model or SAR or SEM (Mussa et al., 2017). LeSage and Pace (2009) introduce the SDM which incorporates the SAR and the SEM in terms of the spatial lags of both the dependent variables and explanatory variables. It states very well in terms of examining the explanatory variables in nearby regions and explains the spatial characteristics of spill-over effects of explanatory variables in neighbouring areas on house prices. Regarding the more flexible in establishing alternative aspects of spatial dependence, the SDM allows capturing direct, indirect and total marginal effects for the explanatory variables representing a more detailed relationships between spatial dependence and explanatory variables. The SDM is more appropriate for establishing the relationships between economic fundamentals and house prices in a spatial circumstance rather than a spatial hedonic model which addresses the house characteristics.

The empirical evidence of advanced performance on SDM in house prices is voluminous (Mou et al., 2018). Osland and Thorsen (2013) investigate the relationship between travel time from the central business district, labour market accessibility and house prices. They find SDM is an appropriate method to link the effects of independent variables in neighbouring regions and house prices. Basu and Thibodeau (1998) illustrate that house prices are correlated spatially in terms of location amenities (e.g., police department, public schools, population with a college degree and distance to employment). Spatial Durbin model is essential for estimating the relationship between economic fundamentals and house prices characterised as spatial data generating processes incorporating spatial dependence among observations (Mussa et al., 2017). Meen (1999) suggest that the fundamentals of migration, equity transfer, information asymmetries and the spatial patterns within house prices are essential in terms of the spill-overs of house prices. Migration or equity assigns to the regions where house prices are comparably low could result in a ripple effect in terms of the increasing demand for houses and thereby house prices (Wang et al., 2017 and Zhang et al., 2014). Information asymmetries illustrate that new information referred to the housing market in one area is transported gradually to other submarkets (Hyuna and Milchevab, 2018). The spill-over effects represent that the explanatory variables of house prices provide a spatial pattern (Mou et al., 2018). However, the application of SDM in the housing market is scarce. House prices are influenced by the determinants in neighbouring areas, but the hedonic method fails to further examine this feature (Huang et al., 2017; Hyuna and Milchevab, 2018; and Yang et al., 2019).

The application of SDM is essential in the Chinese housing market. This is because the explanatory variables of spatial dependence for house prices are different from the other countries due to the transitional economy (e.g., from planning economy to a market-orientated economy). For instance, the abolishment of the Hukou system has encouraged labour mobility between areas and consequently urbanisation caused the equity transfer among regions, and therefore the spatial lag of equity transfer occurs the spatial dependence (Gong et al., 2016). There are other fundamentals affecting the spatial dependence and the spatial patterns of house prices, such as income (Abate, 2017), supply for house (Van Dijk et al., 2011) and unemployment rate (Kondo, 2015), are scarce in the literature of the Chinese housing market (Zhang et al., 2015). In this thesis, research on the driving forces behind the fundamentals of house prices and spatial patterns would be useful in understanding the spatial effects in terms of explanatory variables spill-overs.

2.3.2.2 Models to Capture Spatial Heterogeneity

The existing literature denotes evidence of spatial heterogeneity in the housing market (Meen, 1999; Wood, 2003). The spatial heterogeneity of house price could be caused by spatially varying coefficients across space or spatial regimes (Anselin, 2017). Wood (2003) provides that spatial heterogeneity is caused based on the speed of responses of national economic shocks in one region, where the housing market is more liquid and where new information affects house prices more rapidly than in the neighbouring regions. Accordingly, spatial heterogeneity illustrates that the effects of spatial dependence or determinants on prices are different from that of in nearby regions (Anselin et al., 2008). Therefore, by incorporating the spatial heterogeneity, house prices become stationary structure across space and spatial fixed effect model is applicable.

According to Pijnenburg (2017), given a region specific fixed effects, α, and time period specific effects, ξ, the spatial autoregressive model is sutural stationary incorporating fixed intercepts and time period effects, which is specified as:

$$P = \alpha I_n + \rho WP + \beta X + \xi I_n + \varepsilon \tag{2.16}$$

where P is an $N \times 1$ vector of house price. α is the region specific fixed effects vector of individual fixed effects, with the constraint that $\alpha' I_N = 0$ and stacked by n times, and, as before, $E[\varepsilon\varepsilon'] = \sigma_\varepsilon^2 I_{NT}$. ξ are time period specific effects. I_n is an $N \times 1$ vector of ones. β provides the $K \times 1$ vector of regression coefficients. X represents an $K \times 1$ vector of explanatory variables. $\varepsilon \sim N(0, \sigma^2 I_n)$. W is a $N \times N$ spatial weight matrix.

The spatial fixed effect model is efficient restricting spatial heterogeneity in terms of the fixed region and time period specific effects. For example, Cohen (2016) finds the house prices spill-overs are different between crises times and normal times. Normal times are examined by relatively normal average house price developments, while crisis times are provided by increases or decreases in house prices. The changes of house prices in the alternative time period causes the spatial heterogeneity, which is in line with Wood (2003) providing that spatial heterogeneity is caused by the speed of responses of national economic shocks in one region. On the other hand, spatial heterogeneity is caused by spatially varying distribution of house prices (e.g., with a different mean or variance). Spatial fixed effect model with the fixed region specific effects appropriately decreases the spatial heterogeneity in terms of random effects of house prices.

The extension of the spatial fixed effects model is spatial fixed effects incorporating SDM, which is known as spatial Durbin fixed effect model (Mussa et al., 2017). The spatial Durbin fixed effect model allows for the explanatory variables to capture direct (feedback) effect and indirect (spill-over) effect (Mussa et al., 2017), meaning that the explanatory variables not only have effects from proximity regions but also include effects from distant regions. The spatial Durbin fixed effect model can be defined by:

$$P = \alpha I_n + \rho WP + \beta X + \theta WX + \xi I_n + \varepsilon \tag{2.17}$$

The reduced form of the extended model is given by:

$$P = (I_n - \rho W)^{-1}(\alpha I_n + \beta X + \theta WX) + (I_n - \rho W)^{-1}\xi + (I_n - \rho W)^{-1}\varepsilon \tag{2.18}$$

where P is an $N \times 1$ vector of house price. θ represents the parameters of spatial lag of explanatory variables. α is the region specific fixed effects vector of individual fixed effects, with the constraint that $\alpha' I_N = 0$ and stacked by n times, and, as before, $E[\varepsilon\varepsilon'] = \sigma_\varepsilon^2 I_{NT}$. ξ are time period specific effects. I_n is an $N \times 1$ vector of ones. β provides the $K \times 1$ vector of regression coefficients. X represents an $K \times 1$ vector of explanatory variables. $\varepsilon \sim N(0, \sigma^2 I_n)$. W is a $N \times N$ spatial weight matrix.

The spatial Durbin fixed effect model not only restricts spatial heterogeneity in terms of the fixed region and time period specific effects but also capture direct (feedback) effect by βX and indirect (spill-over) effect by WX (Equation 2.18), which in turn restricts spatial heterogeneity in terms of the spatially varying coefficients of explanatory variables. For example, spatial heterogeneity is caused by spatially varying coefficients of determinants, such as income (Abate, 2017). It implies that the effects of income on house prices in one region are different from that in other regions across space. The spatial Durbin fixed effect model appropriately decreases the spatial heterogeneity in terms of spatially varying coefficients of explanatory variables. In this thesis, the spatial Durbin fixed effect model is employed in evaluating uncertainty of house price for the real options valuation.

In the housing market, the spatial heterogeneity can be examined by the spatial fixed effects model in terms of time period specific fixed effects, spatially varying coefficients of explanatory variables and region specific fixed effects. Wood (2003) provides that spatial heterogeneity is caused based on the speed of responses of national economic shocks in one region, where the housing market is more liquid and where new information affects house prices more rapidly than in the neighbouring regions. By obtaining time period specific fixed effects, the spatial heterogeneity can be examined and spatial fixed effects model is applicable. Meen (1999) argues that heterogeneity arises because of variations in household behaviours and household compositions. Through introducing spatially varying coefficients of explanatory variables, the spatial heterogeneity can be settled and spatial fixed effects model is appropriate.

According to the spatial heterogeneity in terms of spatially varying coefficients of explanatory variables, there is enormous evidence that fundamentals cause the spatial heterogeneity of the house prices and which could be examined by spatial Durbin fixed effect model. The literature analysing the spatial heterogeneity of house prices in terms of unemployment rate provides that the municipal unemployment rates denote significant positive spatial correlation across space (Kondo, 2015). The movement of the population leads to the spill-over effect of the house price which causes the spatial heterogeneity (Zhang et al., 2015). It is mentioned that local government tax is a significant factor to the house price when considering the spatial analysis of house price in China (Liu, 2013). Abate (2017) indicated a rising spatial correlation between house prices and income. Accordingly, fundamentals of house prices cause the spatial correlation of house prices and possibly cause spatial heterogeneity that different effects of same fundamental on house prices in alternative regions across space based on Chow test (Chow, 1960). Therefore, the examination of spatial heterogeneity in terms of spatially varying coefficients of explanatory variables is essential to establish a stationary spatial house pricing model with spatial Durbin fixed effect methodology.

Spatial fixed effect model with region specific fixed effects is employed appropriately to the problems of spatial heterogeneity due to the supply for housing. Meen (1999) illustrates that the spatial heterogeneity of house prices is present due to the supply for housing which is constrained by planning limitations or by geographical restraints by landscape (e.g., lakes, park and rivers). In China, the entire landscape of activity locations decreases the supply for housing but increases the house prices and therefore the spatial heterogeneity is caused by the different distribution of supply for housing across space (Du and Huang, 2018). The distance to the lake influences the house prices significantly and negatively and causes the spatial heterogeneity in West Lake of Hangzhou (Wen and Jia 2004), South Lake of Wuhan (Zhong et al., 2009) and Mouchou Lake in Nanjing (Wu et al., 2008). The spatial heterogeneity due to the supply for housing is also mentioned in distance to the Huangxing Park in Shanghai (Shi and Zhang, 2010), wide port landscape in Hong Kong (Jim and Chen, 2009), accessibility and visibility in Shenzhen (Chen and Jim, 2010) and river accessibility in Guangzhou (Jim and Chen, 2006). The above studies examine the landscape effects on house prices, while the problem that the increasing spatial heterogeneity of house prices in terms of the increasing the housing supply constraints is not mentioned. Therefore, this thesis applies the housing starts as the supply for housing and employs spatial fixed effect model with region specific fixed effects to examine the spatial heterogeneity. In this way, the spatial house prices model is stationary in terms of the introduction of region specific fixed effects in the spatial fixed effect model.

2.3.2.3 Models to Develop Spatial Partitions Techniques

In spatial Durbin model, the explanatory variables can be constructed by direct (feedback) by βX and indirect (spill-over) effects by WX (see Equation 2.18; LeSage and Pace, 2009). The direct effect is present due to the house prices are affected by determinants in the closed nearby regions (e.g., first order neighbourhood). The indirect effect derives from the house prices are affected by determinants in the distant regions (e.g., higher order neighbourhood). However, the influences of explanatory variables are not constructed into a specified order of neighbours in spatial Durbin model.

To deal with this, LeSage and Pace (2010) segmented the influences of direct and indirect effects by partitioning technique which provides a significant impact on spatial econometrics. Jensen and Lacombe (2012) developed this partitioning equation in terms of the spatial model, which is expressed as:

$$\frac{\partial Y_{it}}{\partial X_{kt}} = \left(I - \rho W_{Y_{it}}\right)^{-1}(\beta_k + W\theta_k) \tag{2.19}$$

where

$$\left(I - \rho W_{Y_{it}}\right)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots + \rho^N W^N \tag{2.20}$$

The impacts are relative to each order neighbourhood can be given by:

$$\begin{gathered}\left(I - \rho W_{Y_{it}}\right)^{-1}(\beta_k + W\theta_k) \\ = \underbrace{(I\beta_k + W\theta_k)}_{\mathrm{W}^{(1)}} + \underbrace{(\rho W\beta_k + \rho W^2\theta_k)}_{\mathrm{W}^{(2)}} + \underbrace{(\rho^2 W^2\beta_k + \rho^2 W^3\theta_k)}_{\mathrm{W}^{(3)}} + \cdots\end{gathered} \tag{2.21}$$

$W^{(i)}$ represents the spatial weight matrix of $i^{(th)}$ order neighbours. Regarding to the order of neighbourhood, the lower order $W^{(i)}$ illustrates the closed neighbours, such as first-order neighbours $W^{(1)}$ (Figure 5.3). The higher order $W^{(i)}$ indicates the distant neighbours, such as third-order neighbours $W^{(3)}$.

LeSage and Pace (2009) provide that the distinctions between direct and indirect effects rely on the degree of influence in one region and that of the neighbouring regions, which is in line with the interpretation by Won et al. (2003). In other words, it considers the influences of explanatory variables on house prices from different orders of neighbours. The partitioned direct effects clarify a picture of the spatial feedback effects (Elhorst, 2014). The components of the direct and indirect effects are the essential elements of diagonal matrix (Lesage & Pace, 2010; Elhorst, 2014).

Partitioning technique fills the knowledge gap by exploring the neighbour spatial spill-over effect of determinants on house prices. The previous studies provide the determinants of house prices such as income (Liu and Xiong, 2018), housing supply (Fang et al., 2016), unemployment rate (Drachal, 2016), urbanisation (Garriga et al., 2017) and local government tax (Shi and Lee, 2017). However, these studies have overlooked the spatial spill-over effects of determinants. House prices are affected by determinants of neighbouring price, but the SDM fails to further capture the spatial spill-overs in different order neighbourhood.

The partitioned spill-over effect of determinants on house prices is significant due to two-fold. First, partitioning spill-over effect denotes an in-depth examination into the effects of determinants in different order neighbours on house prices. This examination helps explain the spill-over effects of spatial heterogeneity in terms of spatially varying coefficients. This is because spatially varying coefficients are distributed across space which may spillovers to other regions and causes the possible situation that effects of determinants in higher order neighbourhood on house prices are more significant than that of lower order neighbourhood. Second, the partitioned spill-over effect of determinants on prices contributes the valuable information for housing market regulators. Due to spatially varying coefficients of determinants, such as household income (demand) and building starts (supply), the housing market regulators could adjust the regional demand and supply for housing in order to suggest a stationary development of housing market and encourage the developer to provide a rational house price. Therefore, it is valuable to capture the determinants of house prices in terms of the measures within different geographical regions to the regulators of the housing market. In this thesis, the method employed with partitioned spill-over effect of determinants on house prices is applied to help explain the spill-over effects on spatial heterogeneity.

2.4 Concluding Remarks for Spatial Econometrics in House Prices

A literature review relevant to spatial effects with a focus on house prices is presented. Several studies found that house prices are characterised by spatial correlations, meaning that prices in one area are affected by prices or unknown characteristics in nearby areas (Holly et al., 2011; Pijnenburg, 2017). To examine the spatial correlations, the neighbouring areas are defined by contiguity-based approaches. Two types of spatial effects were found in the Chinese housing market. First, spatial dependence effect on house prices was found that house prices depend on prices or unknown characteristics in neighbouring regions. Second, spatial heterogeneity effect on prices was captured in terms of prices in nearby areas are affected in a different way by the same factors.

Regarding univariate models of spatial effects on house prices, Global Moran's I model determines the existence of the spatial autocorrelation in the model residuals. However, Global Moran's I model provides a misleading result when the spatial structure of a process varies from one area to another because it measures the average level of spatial autocorrelation across the obtained insights (Lloyd, 2007). Therefore, the purpose of spatial heterogeneity test has transferred from Global Moran's I model to Local Moran's I model which examines characteristics across space and local privileges. Index Moran' I is generally employed in spatial econometrics to test the similarity or dissimilarity (positive correlation, negative correlation) of house prices in spatial analysis (Helbich et al., 2014). This is because house prices have spatial autocorrelation in space (Baumont, 2004). In this thesis, the Moran' I model will be one of the competing models, although we look forward to including specified spatial autoregressive models which reject the null hypothesis (e.g., spatial lag or spatial error).

In terms of the multivariate models of spatial effects on house prices, the SAR, SEM and SAC models examine the spatial dependence of house prices depending on where the autoregressive process is to present. These models overcome the OLS regression in terms of the efficient spatial parameter estimators and unbiased spatial variance estimators. This circumstance provides the correct confidence intervals based on estimated parameter and variance leading to correct predicted house prices. In this thesis, the spatial autoregressive and spatial error component are essential to be examined by SAR and SEM in understanding the spatial spill-overs of house prices in China. This is because spatial dependence of house prices is also known as spill-over effects referred to the literature of spill-over effects in the Chinese housing market (see in section 2.3.2). The spill-over effects of housing market in China are significantly different from that of other countries in terms of the different city sizes of polygons and the varying development states of cites across the country.

The extension of the spatial autoregressive model is spatial Durbin model (SDM) which is a generalisation of SAR and SEM model which also includes spatial correlation of explanatory variables. The SDM investigates more spatial interactions rather than spatial hedonic model or SAR or SEM in terms of the additional spatial lags of explanatory variables. Regarding the more flexible in establishing alternative aspects of spatial dependence, the SDM allows capturing direct, indirect and total marginal effects for the explanatory variables representing a more detailed relationships between spatial dependence and explanatory variables. The SDM is more appropriate for establishing the relationships between economic fundamentals and house prices in a spatial circumstance rather than a spatial hedonic model which addresses the house characteristics. In this thesis, SDM is employed in the house prices investigation in China due to the driving forces behind the fundamentals of house prices and spatial patterns, which is valuable in understanding the spatial effects in terms of explanatory variables spill-overs.

Spatial fixed effect model is applicable to capture the spatial heterogeneity in terms of the fixed region specific effects and time period specific effects. However, spatial fixed effect model fails to examine spatial heterogeneity in terms of the spatially varying coefficients of housing determinants. The extension of the spatial fixed effects model is spatial Durbin fixed effect model which additionally allows for the explanatory variables to capture direct (feedback) effect and indirect (spill-over) effect. In this way, the spatial Durbin fixed effect model appropriately decreases the spatial heterogeneity in terms of fixed region specific effects, time period specific effects and spatially varying coefficients. In this thesis, the spatial Durbin fixed effect model is employed in evaluating uncertainty of house price for the real options valuation.

Partitioning technique fills the knowledge gap by exploring the neighbour spatial spill-over effect of determinants on house prices. House prices are affected by determinants of neighbouring price, but the SDM fails to further capture the spatial spill-overs in different order neighbourhood. The partitioned spill-over effect of determinants on house prices is significant due to two-fold. First, partitioning spill-over effect denotes an in-depth examination into the effects of determinants in different order neighbours on house prices. Second, the partitioned spill-over effect of determinants on prices contributes the valuable information for housing market regulators. In this thesis, the method employed with partitioned spill-over effect of determinants on house prices is applied to help explain the spill-over effects on spatial heterogeneity.

2.5 Characteristics of Real Options in the Real Estate Market

Several studies have provided that real options help evaluate investments in land development whenever there is uncertainty that can affect investment decisions, at the same time, there is flexibility to alter or to expand this investment (Čirjevskis and Tatevosjans, 2015; Rocha et al., 2007; Ross, 1978). The uncertainty in vacant land development was found in the Chinese real estate market in terms of the underlying house price on vacant land. The flexibility in uncertainty about underlying house price on vacant land was revealed such as effects of risk or underlying building units. Uncertainty about underlying house price decreases investment activity in the current period but increases the land value (Razak et al., 2018; Sing and Patel, 2001).

Previous studies have suggested the characteristics of real options in vacant land development in terms of uncertainty (Capozza and Schwann, 1990; Titman, 1985). Referred to these studies, the uncertainty is due to the underlying house price. For example, underlying house price can be affected by unsystematic risks (Capozza and Schwann, 1990) and underlying building units (Quigg, 1993) which are flexible and drives the uncertainty. The underlying house price must be estimated because the price is intangible for the future building on vacant land (Quigg, 1993). The uncertainty about underlying house price, $\sigma_{\varepsilon\prime}^2$, can be measured based on the prior house prices determinants by OLS method, which is given as:

$$P = \alpha + \beta X + \varepsilon \tag{2.22}$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2) \tag{2.23}$$

where P is house price. α is an intercept. β provides the $K \times 1$ vector of parameter of house prices determinants. X represents an $K \times 1$ vector of explanatory variables. ε is a $N \times 1$ vector of error. N and K are the number of observations. The contributions of house price, β, are allowed to vary time and region, respectively. According to the resulting parameter β, the prediction of the underlying house price is specified as:

$$P' = \hat{\alpha} + \hat{\beta}\bar{X} + \varepsilon' \tag{2.24}$$

$$\varepsilon' \sim N(0, \sigma_{\varepsilon\prime}^2) \tag{2.25}$$

where P' is underlying house price. $\bar{X}$ is a vector of house price determinants. $\hat{\alpha}$ is an estimator of intercept. $\hat{\beta}$ is an estimator of coefficients.

The flexibility in uncertainty about underlying house price on land development is various. For instance, Cunningham (2007) provides that the quality-adjust house prices can be estimated (e.g., transformation of $\bar{X}$ with region and land characteristics in Equation 2.22) in contrast with the underlying house price with OLS estimator. Capozza and Schwann (1990) illustrates that the influences of systematic and unsystematic risk (e.g., transformation of $\bar{X}$ with risk-adjusted growth rate) are significant on underlying house price for converting agricultural land. Quigg (1993) suggests that the flexibility of the underlying building units (e.g., transformation of $\bar{X}$ with height and size of underlying building) differs the price of underlying constructions. These studies have approved the applications of the flexibility in uncertainty about underlying house price, meaning that the less confident developers become about the underlying house prices, the greater the gap will be between future profits from building at the actual price and those from building at the expected price (Yu and Hui, 2018).

The uncertainty about underlying house price on land development decreases the investment activity in the current period (e.g., Razak et al., 2018; Sing and Patel, 2001). Deferring land development may reveal further information which will affect the underlying house price (Childs et al., 2002). Once the future information is received and the uncertainties are identified, the optimal decision can be made by investment (Fan et al., 2018). For this reason, the proportional hazard model evaluating the timing of land development function is defined by:

$$h(t) = h_0(t)\exp(\delta L) \tag{2.26}$$

$$\delta L = \alpha + \gamma E[P'] + \varphi\sigma_\varepsilon^2 + \beta X + \nu \tag{2.27}$$

where the expected house price is $E[P']$. σ_ε^2 represents the price uncertainty. X is the vector of explanatory variables. ν is an error term. The null hypothesis is that price uncertainty does not affect the timing of land development, which is present $H_0: \gamma = 0$; and the alternative hypothesis is that price uncertainty defers the timing of land development, presenting $H_a: \gamma < 0$.

Several studies have documented that the uncertainty about underlying house price increases the land value (Grovenstein et al., 2011; Tsekrekos and Kanoutos, 2013). Price uncertainty increases the option premium on land and causes the land to be more valuable with alternative uses than it does for immediate development (Quigg, 1993). If there is a greater level of price uncertainty according to the further information, then the vacant land will be traded at a premium above discounted future rents in current low capital use (Cunningham, 2006). To test the effects of price uncertainty on land value, a regression model of vacant land is specified as:

$$L = \alpha + \alpha_1\sigma_{\varepsilon'}^2 + \alpha_2 E[P'] + \beta X + \upsilon \tag{2.28}$$

where L is vacant land price. The expected house price is $E[P']$. σ_ε^2 represents the price uncertainty. X is the vector of explanatory variables. ν is an error term.

With respect to successfully apply real options into land development investment it is suggested that the uncertainty about underlying house price are examined by the various models under the flexibility. Modelling empirical price uncertainty are mentioned in prior studies (Titman, 1985; Cunningham, 2006; Capozza and Helsley 1990; Capozza and Schwann 1990; Quigg, 1993). Such modelling has been contributed in terms of hedonic model, adjusted house price model, proportional hazard model, GARCH model and OLS model. There are numerous applications of these models to modelling house and land data including estimating and forecasting underlying house price and its uncertainty (Chiang et al., 2006; Cunningham, 2006; Grovenstein et al. 2011; Quigg, 1993; Razak et al., 2018; Shi et al., 2015; Tsekrekos and Kanoutos, 2013). However, there is no undisputed method that deals with uncertainty about underlying house price in the most appropriate approach in the Chinese real estate market (Chiang et al., 2006). A typical approach suggests that various models are critically examined and evaluated, both in-sample and out-of-sample. In remainder of this chapter, several models of real options valuation, underlying house price, uncertainty and timing of land development are presented. Moreover, the application of real options in other sectors of economy (e.g., agriculture, R&D-intensive, pharmaceuticals, natural-resource, electricity and investment appraisal) is reviewed, although we do focus on real options approach applied to the real estate market.

2.6 Real Options Approach in the Real Estate Market

Based on the theoretical and empirical literature (see in Section 2.6), various models are capable to examine the uncertainty about underlying house prices and its effects on the timing of land development and land prices. These models are appropriately motivated to value the real options premium in terms of uncertainty and flexibility.

2.6.1 Model of Land Development

Cunningham (2006) provides a framework to explain the decision on land development in terms of the future use of land. The profit of new land development is specified as:

$$\pi = P_i - C_i - R \tag{2.29}$$

where π is the profit of a new development of land. P_i is the house price at location i. C_i is cost the of house location i. R is the land rent. In order to deal with the optimum amount of land capital at location i, R_i estimates the equilibrium land ren oft. When the profit is equative to zero, the modified formula of land rent is written as:

$$R_i = P_i - C_i \tag{2.30}$$

When the land value at location i, which has newly established houses, is more than the value of land as it is currently used, the land will be developed for construction. The landowner makes a decision as below:

$$\begin{array}{ll} \text{if } R_i \geq R_{current}, & \text{build} \\ \text{if } R_i < R_{current}, & \text{do not build} \end{array} \tag{2.31}$$

Regarding the purpose of this model, $R_{current}$ is concerned as the discounted future rent of land. However, if the future house price at location i is uncertain, the optimal land capital, m, will be referred to today's price information. The current house prices in the neighbouring regions have an ability to inform the level of investment in the future. When the market values this information, there should remain a real-option premium, C (Equation 2.42), on undeveloped land. These option premiums may delay the building activity. Accordingly, the modified decision with option premium by landowner is written as:

$$\begin{array}{ll} \text{if } R_m \geq R_{current} + C, & \text{build} \\ \text{if } R_m < R_{current} + C, & \text{do not build} \end{array} \tag{2.32}$$

where R_m represents the land rent at the optimal land capital. Thus, the increase of option premium delays the building activity, while the decrease of option premiums encourages the land development. However, to successfully determine the presence of real options premium requires predictions of underlying house prices and examinations of uncertainty about underlying house prices.

2.6.2 Models of House Price Uncertainty

There is no unanimous method that the most appropriate modelling approach deals with the uncertainty about underlying house prices. The previous studies examine the observed volatility of house prices over the recent past based on the flexibility of underlying house prices (Tsekrekos and Kanoutos 2013; Yao and Pretorius, 2011). We applied a similar approach but our analysis is further complicated in two-fold. First, the estimation of the underlying house prices considers the effects of neighbouring determinants with spatial Durbin fixed effect model. Second, the observed volatility of house prices is transformed into implied volatility of underlying house prices with a generalized autoregressive conditional heteroskedasticity (GARCH) model.

2.6.2.1 Forecasting Underlying House Prices

To measure the house price uncertainty, the underlying house price must be estimated firstly because the price is intangible for the future building on vacant land (Quigg, 1993). In order to consider the effects of neighbouring determinants on underlying house prices, the spatial Durbin fixed effect model (Equation 2.17) is applicable, which contains the parameters of neighbouring house prices, neighbouring explanatory variables, neighbouring unknown characteristics and region and time period specific effects. Based on the estimation of parameters (in Equation 2.17), the formulation of underlying house prices is expressed as:

$$P_{it}' = \widehat{\alpha I_n} + \hat{\rho} \sum_{j=1}^{N} W_{ij} P_{it} + \widehat{\beta_k} \sum_{k=1}^{k} X_{itk} + \widehat{\theta_k} \sum_{k=1}^{k} \sum_{j=1}^{N} W_{ij} X_{jtk} + \widehat{\xi I_n} + \widehat{\upsilon_{it}} \quad (2.33)$$

$$\widehat{\upsilon_{it}} \sim N(0, \sigma_{\upsilon_{it}}^2 I_n) \quad (2.34)$$

$$\widehat{\upsilon_{it}} = \hat{\lambda} \sum_{j=1}^{N} W_{ij} \upsilon_{it} + \varepsilon_{it} \quad (2.35)$$

$$\varepsilon_{it} \sim N(0, \sigma_{\varepsilon_{it}}^2) \quad (2.36)$$

where P_{it}' is a $N \times 1$ vector containing one observation of the dependent variable for each spatial element ($i = 1, \ldots, N$). N is the number of regions. t represents the observation at time t. $\hat{\rho}$ provides the estimator of spatial lag parameter. $\hat{\lambda}$ illustrates the estimator of spatial error parameter. X_{it} represents the vector of explanatory variables and consists of a $N \times K$ matrix. K is the number of explanatory variables. $\widehat{\beta_k}$ provides the estimators of K explanatory variable coefficients. $\widehat{\theta_k}$ represents the estimator of parameters of explanatory variables spatial lag. I_n is an $N \times 1$ vector of ones. α is the region specific fixed effects vector of individual fixed effects. ξ are time period specific effects.

The spatial Durbin model applied to underlying house prices is due to the price determinants in nearby areas (spatial lags of explanatory variables) which are mentioned in forecasting house prices (Case and Shiller, 1989; Cunningham, 2006). The advanced spatial Durbin fixed effect model not only incorporates the SAR and the SEM in terms of the spatial lags of both the dependent variables and explanatory variables but also captures spatial heterogeneity in terms of spatially varying coefficients within region and time period specific effects (see details in Section 2.3.2.1 and 2.3.2.2). In contrast with the prior studies, the OLS estimator is applied to the underlying house prices (Capozza and Helsley, 1990; Capozza and Schwann, 1990; Grovenstein et al., 2011; Razak et al., 2018). The neglect of spatial lags on OLS regression leads to the unbiased results but inefficient parameter estimators and biased variance estimators (Anselin, 2014). In this thesis, the spatial Durbin fixed effect model is applied to underlying house prices in order to forecast the house price within a spatial consideration.

2.6.2.2 Measuring Uncertainty about Underlying House prices

The GARCH model is appropriate to measure the volatility of house prices (Lee and Reed, 2013; Miles, 2008, 2011; Willcocks, 2010). Proposed by Bollerslev (1986), the GARCH model allows the error variance to depend on its own lags and lags of the squared error. By this way, the conditional variance follows an Auto Regressive Moving Average (ARMA) process. In a special case, GARCH(1,1) model can be processed due to the assumption that current volatility is affected by previous innovation to volatility (Miles, 2008). By obtaining the conditional variance process, the volatility of house prices become stationary. The mean equation of GARCH model is given by:

$$P'_{it} = \alpha_i + \beta_i P'_{it-1} + \varepsilon_{it} \tag{2.37}$$

where P'_{it} is underlying house prices. α_i is a intercept. t is the house price at time t. The uncertainty about underlying house price, σ^2_{it}, which is provided by the error variance equation of GARCH(1,1) model, is expressed as:

$$\sigma^2_{it} = a + \gamma \varepsilon^2_{it-1} + \theta \sigma^2_{it-1} \tag{2.38}$$

where σ^2_{it} and ε^2_{it} are the conditional variance process.[10]

The influence of the GARCH model in forecasting house prices volatility is abundant. Cunningham (2006) provides that the price uncertainty (σ^2_{it}) increases when GARCH estimation includes the one-year-ahead house price. Enormous studies including Lee and Reed (2013) and Willcocks (2010) have suggested similar conclusions. The investors' confidence in the one-year-ahead price forecast is stipulated on the accuracy of price forecasts in the recent past. The estimation of the error variance of residuals suggests the developers have additional information that is influencing the price (Lee and Reed, 2013). The factor, which is leading market house price, might be recognised more by developers through σ^2_{it} (Miles, 2008). The advance of the GARCH model, in the field of house prices,

[10] For a survey of the detailed and more available GARCH models and their extensions, see Bauwens et al. (2006).

compared to the ARCH model is present in terms of the more restricted lag structure successfully capturing the dependencies in the conditional moments (Miles, 2011). Regarding the real options approaches, this thesis employs σ_{it}^2 of GARCH model as house price volatility.

2.6.3 Price Uncertainty and Timing of Land Development

The previous studies suggest that the proportional hazard model is appropriately employed to examine the effects of house price uncertainty on the timing of land development (Bulan et al., 2009; Cunningham, 2006; Shi et al., 2015). The proportional hazard model examines the function of timing of land development $h(t)$. In other words, the land will 'dies' when a building is constructed on it. The length of time, which is from presale permit to developers to put the houses on the market for sale, depends on the baseline hazard model assumption, $h_0(t)$, and a vector of covariates, Z. Regarding the spatial lags of land prices and explanatory variables, this thesis incorporates the spatial Durbin model into the proportional hazard model, which is specified as:

$$h(t) = h_0(t)\exp(\delta Z) \tag{2.39}$$

where the baseline hazard, $h_0(t)$, is shifted by a vector of covariates, Z. The covariates are specified as:

$$\delta Z = \gamma E[P'] + \varphi\sigma_\varepsilon^2 + \rho WL + \beta X + \theta WX + \xi I_n \tag{2.40}$$

where $E[P']$ is underlying house prices. σ_ε^2 is uncertainty about underlying house price. ρ is the spatial lag parameter of land prices. β represents the coefficients of explanatory variables. θ is the spatial lag parameter of explanatory variables. W is a $N \times N$ spatial weight matrix. L is land price. X represents a vector of land price explanatory variables. ξ are time period specific effects. I_n is an $N \times 1$ vector of ones.

The empirical application of the proportional hazard model to the timing of land development is voluminous (see for example Bulan et al., 2009). Bulan et al. (2009) employing 1214 land transaction data in Canada from 1979 to 1998 finds a one-standard-deviation leads to a 13% decline in the likelihood of land development. Cunningham (2006) examines the real estate transaction data based on GIS records between 1982 and 2002 in Seattle and provides the increase of a one-standard-deviation declines the likelihood of development by 11%. Shi et al. (2015) using 281,405 apartments transaction data in Beijing between 2006 and 2008 provides a one-standard-deviation will defer apartment to sale by 0.56%. However, these studies did not consider the spatial effects on land prices. Basu and Thibodeau (1998) illustrate that lack of spatial effects leads to the inefficient parameter estimators and biased variance estimators. In this circumstance, estimated parameters are in the incorrect confidence intervals. Therefore, this thesis contributes to the proportional hazard model in terms of the incorporation of spatial Durbin model which not only considers the time specific fixed effects but also contains the spatial lags of land price and its explanatory variables.

2.6.4 Uncertainty and Land Prices

To test the presence of real options in land markets, the effects of underlying house price and its uncertainty on land prices are examined by OLS estimator, which is given by:

$$L = \alpha + \alpha_1 E[P'] + \alpha_2 \sigma_\varepsilon^2 + \beta X + \varepsilon \tag{2.41}$$

where L is land price. α is an intercept. α_1, α_2, and β are regression coefficients. X represents a vector of explanatory variables. ε is an error term.

Referred to Equation 2.32, the uncertainty about underlying house prices increased the option premium on land providing the current (e.g., non-housing) use more valuable than immediate building activities. If there is a greater level of price uncertainty according to the economic information, then the vacant land will be traded at a premium above discounted future rents in current low capital use, $R_{current}$.

The empirical evidence that uncertainty about underlying house price increases land value is plentiful (see for example, Cunningham, 2006, among others). Yu and Hui (2018) employs house and land data from 1995 to 2016 in Hong Kong and finds that the investment that operates a real asset can increase the underlying value which also raises the value of land. The similar conclusion is expressed by Chiang et al. (2006), Grovenstein et al. (2011), Quigg (1993), Razak et al. (2018), Sing and Patel (2001), Tsekrekos and Kanoutos (2013) and Yamaguchi et al. (2000). In this thesis, the OLS estimator is applied to test the relationship between uncertainty about underlying house prices and land prices.

2.6.5 Model of Real Options Valuation

The European-style options pricing equilibrium model is first developed by Fischer Black (1973) and Myron Scholes (1973), which is called 'Black-Scholes' model (Cox et al., 1979).

This model is appropriately employed to deal with real options premium with an underlying asset (Vahdatmanesh and Firouzi, 2017). Black and Scholes adopt the valuation of European call and put options on the potential future values of the underlying asset in terms of a 'Weiner process' and 'Geometric Brownian Motion' (Crundwell, 2008; Lander and Pinches 1998). Developing vacant land at a premium is analogical to exercise a call option (Dixit and Pindyck, 1994; Pindyck, 1991; Razak et al., 2018). Thus, the valuation equation of a European call option is employed, which can be expressed as:

$$C = SN(d_1) - N(d_2)Ke^{-rt} \tag{2.42}$$

$$d_1 = \frac{\ln\left(\frac{S}{K}\right) + (r + \frac{\sigma^2}{2})t}{\sigma * \sqrt{t}} \tag{2.43}$$

$$d_2 = d_1 - \sigma * \sqrt{t} \tag{2.44}$$

where C is call option premium. S represents the value of the underlying asset. t is time until option exercise. K provides option striking price. r is the risk-free interest rate. N is the cumulative standard normal distribution. e is the exponential term. σ is the volatility of underlying asset price. ln is a natural log.

Ross (1978) and Rocha et al. (2007) provide that Black-Scholes model valuing the real options premium on vacant land overcomes the traditional capital budget (e.g., forecast the expected cash flows, discount cash flow at the cost of capital and subtract the amount of the investment). The assumptions of the DCF method suggest the estimated future cash flows can be estimated on the premise of future certainty, which is short-sighted decisions, underinvestment and loss of competitive position in terms of the lack of uncertain strategic considerations (Keswani and Shackleton, 2006; Trigeorgis and Mason, 1987; Zeng and Zhang, 2011). In contrast, Black-Scholes model for real options has been applied to land development to account for the uncertainty based on the flexibility, volatility of uncertainty and timing of land development, where the traditional DCF is unable to do so (Tsekrekos and Kanoutos, 2013). For instance, Patel and Sing (2000) incorporate the house price uncertainty on the decision of land development and demonstrate that the traditional DCF model tends to encourage the building activity at the premature time; however, real options model inspires that the development should be postponed in terms of the uncertainty about underlying house price. In this thesis, the Black-Scholes model is employed to value the real options premium on vacant land.

The empirical evidence that land has a premium in the real options valuation is voluminous in various countries. Quigg (1993) employing the real estate transaction data between 1976 and

1979 and in Seattle finds that there is a 6% option premium on undeveloped land. Cunningham (2006) examines the real estate transaction data based on GIS records between 1982 and 2002 in Seattle and provides the increase of a one-standard-deviation raises vacant land prices by 1.6%. Chiang et al. (2006) using 58 lands auctions and 3,500 real estate transactions from 1995 to 2001 in Hong Kong illustrate the option premium on vacant land varies between 2.33% and 69.1%, with an average of 7.75%. Grovenstein et al. (2011) provide that the premium is 6.6% in the option to delay using 2,034 properties transactions data and 836 vacant land transactions data from 1986 to 1993 in Chicago. Tsekrekos and Kanoutos (2013) investigate the real estate market in Greece between 2004 and 2007 and show a premium on the option to wait is between 26.66% and 52.38%, especially in the west and north suburbs of Athens. Razak et al. (2018) investigate the option of speculative behaviour for vacant land delays the building activity in Malaysia by 254 vacant land plots and 3,681 houses in Malaysia from 2010 to 2013 and finds the option premium on vacant lands ranges from 8% to 20% across all areas in Selangor, Malaysia. The option premium has been found to be 16% to 28% in the United Kingdom between 1984 and 1997 (Sing and Patel, 2001), 18.5% and 36.5% for Tokyo from 1986 to 1993 (Yamaguchi et al., 2000). However, the empirical evidence of option premium on land is lack. In this thesis, we incorporate the models mentioned above to examine the option premium on land in the Chinese real estate market.

2.7 Real Options Approaches in Various Industries

Schwartz and Trigeorgis (2004) suggest that there are six categories of real options approaches under conditions of uncertainty and differences in flexibility, which are option to defer, time-to-build option, option to alter operating scale, option to abandon, option to switch and corporate growth option. According to the categories of real options, this section reviews the real options approaches applied to the various sectors of the economy.

2.7.1 Option to Defer Investment

Trigeorgis (1996, p. 10) describes the option to defer investment as an option to buy valuable land or resources. This option allows the developers to wait x years in order to explore the justification between the output prices and development costs. The value of investment opportunity C is given by:

$$C = \max(V - I_x, 0) \tag{2.45}$$

where V is the value of project. I represents the project's outlays. The option to defer is thus similar to call option on gross present value, V, with strike price, I_x (Titman, 1985). Trigeorgis (1993) emphasises that the additional investment opportunity in the NPV rule decrease the value of option the to wait unless the value of cash flows, V, exceeds the outlays, I_x, by a substantial premium in terms of the uncertain characteristic.[11]

In terms of the option to defer, Bernanke (1983) illustrates that the uncertainty of investment delays the investment activity, particularly on real asset investment due to the type of investment is irreversible. Dixit (1989) and Dixit and Pindyck (1994) provide a similar conclusion to Bernanke (1983). Titman (1985) establishes the option pricing model, which was initially employed by Black and Scholes (1973) and Merton (1973), to investigate the option value of vacant plots of land under the uncertainty about underlying house price due to the flexibility the underlying building units. It is found that the uncertainty decreases the investment activity in the current period resembles Bernanke (1983). Ingersoll and Ross (1992) provide that the investment should not be undertaken until the project rate of return is substantially exceed of its break-even rate in terms of the uncertain interest rate.

Agriculture decisions have the option to defer based on the investment is essentially irreversible or severe to be changed once have been made. (Köppl-Turyna and Köppl, 2013). Sanderson et al. (2015) treat transformations and infrastructure as underlying assets, which are irreversible, and investigate real options of Australian wheat production under climate change. They find that the option to defer is valuable under uncertainty about the climate which delays the adaptation and transformation of agricultural systems. An application to greenhouse construction provides strong support for the implementation of 2328/91 EU regulation in real options, as the adoption of new technology in greenhouse building is inefficient without regulation (Tzouramani and Mattas, 2004). It implies that the real options change the investment decisions in terms of the regulatory uncertainty and greenhouse construction (irreversibility) in the agricultural industry.

[11] Net Present Value (NPV) rule is "invest when the value of a unit of capital is at least as large as the purchase and installation cost of the unit" (Pindyck, 1998).

Köppl-Turyna and Köppl (2013) overview the studies of the applications of real options in agriculture and provide that policymakers should improve the method of cost-benefit analysis (e.g., sunk costs) because these policies influence the flexibility and uncertainty about outputs volatility.[12] Seyoum and Chan (2012) investigate wine grape farm investment in North West Victoria and demonstrate that the sunk costs and volatile seasonal revenues for wine grape farming have a significant option value in waiting. Coratoa and Brady (2019) also consider that sunk investment costs and uncertain about returns increase the value of option to wait based on the effects of decoupled payments on the optimal timing of agricultural land development.[13] The results provide that decoupled payments stimulate the activity of development while passive farming increases. In other words, decoupled payments influence the managerial flexibility in terms of the option to wait. It also suggests that policymaker should regulate passive farming based on supporting optimal returns for the investors and decreasing the potential capitalisation of the Basic Payment Scheme (BPS) payments in land values and rental prices.

2.7.2 Time-to-Build Option

The time-to-build option is described as the option to default during staged construction (Trigeorgis, 1996, p. 11). The staging investment as a series of outlays creates options to abandon at any stage. Each stage of the capital investment is treated as an option on the value of subsequent stages by instalment-cost outlay or for the next stage. In this process, the option is valued as a compound option resembles options on options. Carr (1988) examines sequential compound options and suggested the time-to-build option resembles the options to acquire subsequent options to exchange an asset for another asset. Majd and Pindyck (1987) examine the time-to-build option for an irreversible investment which has an option to postpone at each stage of the project. The optimal decision at each period is either to invest at a maximum rate or wait for an improvement in external conditions.

Time-to-build option has flexibility on each stage decision in R&D-intensive industries, particularly in pharmaceuticals. Hartmann and Hassan (2006) provide that the real options approach emphasises in the clinical phases by the pharmaceutical companies and is different

[12] Pindyck (1991) provides that cost of investment can be a sunk cost, which is unrecovered.

[13] "Decoupled payments are budgetary payments paid to eligible recipients which are not linked to current production of specific crop or livestock numbers or the use of specific factors of production" (Coratoa and Brady, 2019).

from financial service firms who focus on the pre-clinical phase. Real options provide a more holistic project analysis in terms of flexibility in the strategic phases. Within clinical phases, the pharmaceutical companies have the opportunities to capture future uncertain characters based on which to make the next strategic investment decision.

Time-to-build option is also valuable in a new technological area which is affected by the scope of the technological opportunity, the competition in the area, and a firm's past investment behaviour (Baranova and Muzykob, 2015; Hamill et al., 2013; McGrath and Nerkar, 2004). McGrath and Nerkar (2004) suggest that time-to-build option is essential in the U.S. pharmaceutical industry in terms of the uncertainty about next stage in a new technological area because there are advantages on past investment behaviour and reduced competition decreases the cost of new technological investment. The uncertainty about next stage increases the value of option to develop the investment. The investment in next stage is more profitable due to the last investment. Baranova and Muzykob (2015) evaluate a methodological approach on the influence of venture capital investments in innovative projects in pharmaceutical industry and provide that the compound real option raises the overall value of the innovative project based on the factor of staged investment and a possibility to stop financing. Hamill et al. (2013) examine the shareholder wealth effects on the United States Food and Drug Administration (FDA) for firms and provide that the FDA for drug approvals significantly increase shareholder wealth. The increase in shareholder wealth is due to the enhancements of existing drugs and information leakage. These studies demonstrate the uncertainties (e.g., new technological area and information leakage) have a positive impact on the option value in pharmaceutical R&D-intensive industry.

In terms of long-term projects, the time-to-build option has a value in terms of capital budgeting on each stage. Karami and Farsani (2011) illustrate that the real options method shows lower the escalation of commitment (EC)[14] for a failed project than those who merely use the net present value method. It implies that employing the real options on capital budgeting of each stage can influence investors' behaviour and decisions in terms of better decision-making in long-term projects.

[14] See 'real option method and escalation of commitment in the evaluation of investment projects' by Karami and Farsani (2011).

2.7.3 Option to Alter Operating Scale

Based on the expected market conditions, there are the options for the firms which can expand the scale of production and advance the resource utilisation or reduce the scale of operations or shut down and restart the project due to the risk and uncertainty (Trigeorgis, 1996, pp. 11-12).

2.7.3.1 Option to Expand

When the market conditions are more favourable than expected, there is an option to expand the scale of operation (by $x\%$) with a subsequent cost (I_E). Trigeorgis and Mason (1987) noted the option to expand is analogous as a call option which stock price is the sum of base-scale value and additional part ($x\%$) and the exercise price is (I_E). The value of investment opportunity, C, is expressed as:

$$C = V + \max(xV - I_E,\ 0) \tag{2.46}$$

The option to expand is valuable in the oil industry. The management applied a more expensive technology to expand production in terms of built-in flexibility such as oil (Sabet and Heaney, 2017). Sabet and Heaney (2017) examine the link between oil (gas) firm share price and crude oil (natural gas) return, volatility and drilling activity. They provide that real options influence the drilling by gas firms. Also, the exercise of option to expand has affected the firm share price. This result supports the possibility of compound option effects referred to the built-in flexibility between drilling and firm share price.

The option to expand is essential to strategic operations, particularly if it enables the firm to capitalise on future growth opportunities if future market developments yield favourable (Trigeorgis, 1990). Trigeorgis (1996, p. 11) finds that an option for future growth is significant in terms of buying vacant land to position the advantages of developing market share.

2.7.3.2 Option to Contract

The option to contract occurs that the management reduce the scale of the project (by $c\%$) with saving part of the planned investment outlays (I_C) when the market conditions is weaker than expected. Trigeorgis (1996, p. 11) provides the options to contract resembles the option to expand in terms of the flexibility to mitigate loss the of a project, which the stock price is the base-scale project minus mitigate part (c%) and treat the potential cost savings (I_C) as the exercise price. The option premium, P, can be given by:

$$P = \max(I_C - cV, 0) \tag{2.47}$$

In contrast with the option to expand, the option to contract is significant to the project for introducing new products in uncertain markets (McGrath and Nerkar, 2004). The option to contract is emphasised in choosing among technologies or plants with alternative ratios of construction cost to maintenance cost. It is appropriate to construct a plant with lower initial development costs and higher maintenance expenditures due to the flexibility on contract operations when the market conditions go down (Fonseca et al., 2017).

2.7.3.3 Option to Shut Down and Restart Operations

In terms of the option to shut down and restart operations, the operation in each year is regarded as a call option to acquire that year's cash revenues (C) by paying the variable costs of operating (I_V) as exercise price (Trigeorgis, 1996, p 11). The option premium, P, is expressed as:

$$P = \max(C - I_V, 0) \tag{2.48}$$

Option to shut down and restart operations is the right to acquire each year’s cash revenues by paying the variable costs of operating and then achieve the optimal premium (Fonseca et al., 2017). It is typically found in natural-resource industries. A seminal study examining the option value on a copper mining project with high-risk cash flow provides that the uncertainty is considered in the payoff (Brennan and Schwartz, 1985). The results provide that the continues time arbitrage and stochastic control theory are applicable to determine the optimal decisions for developing, managing or abandon. Fonseca et al. (2017) incorporate managerial flexibility on an African oil exploration project and demonstrate that the uncertainty about oil price volatility decreases the optimal returns in a Monte Carlo simulation (MCS). While the result considering managerial flexibility in the binomial model provides that the uncertainty about oil price volatility increases value for the project. It implies that the option to shut down and restart operations achieve the optimal premium in terms of the uncertainties about cash income in the oil industry.

2.7.4 Option to Abandon for Salvage Value

Trigeorgis (1996, p. 12) concludes that management owns the right to abandon current operations permanently and comprehend the resale value of capital assets on second-hand markets for its salvage value in terms of the option to abandon when the market conditions decline significantly. This option can be treated as an American put option on the current value of the project (V) with an exercise price the salvage or best-alternative-use value (A). The option premium, C, is given by:

$$C = V + \max(A - V, 0) \tag{2.49}$$

or

$$C = \max(V, A) \tag{2.50}$$

Clark et al. (2010) employing an option-pricing model for valuing the abandonment option from UK divestitures from 1985 to 1991 find the abandonment option to investors is based on private information, which is the actual exit value. It suggests overpricing is associated with the premature investment.

Valuable abandonment options are found in the capital-intensive industries (Myers and Majd, 1990). Capozza and Li (2002) explore the land development decisions with the consideration of capital intensity (e.g., current yield and internal rate of return, IRR) and find there is the optimal investment when the current yield is equative to the cost of capital plus uncertainty premium in the real options valuation. The IRR balanced the sum of the cost of capital and the uncertainty premium of cash flows' growth rate. The increase of interest rate decreases the optimal capital intensity in terms of the positive response of project IRR and accelerates the investment activity. It implies that the growth of cash flows delays the optimal projects which are influenced positively under the growth of uncertainty and decreases the optimal capital intensity in terms of an option to abandon for salvage value.

2.7.5 Option to Switch Use

If there are changes in prices or demand, management can change the facility output mix (product flexibility); alliteratively, the same outputs can be produced using different types of inputs (process flexibility, Trigeorgis, 1994).

In terms of the option to switch in workforce expansion, treating shifts on workforce expansion is an investment opportunity (Fernandes et al., 2013). Referred to the traditional

DCF, the decision on increasing shifts by employing temporary workers or hiring permanent employees is at risk because the idiosyncrasies in shift management are captured slightly. In contrast, real options provide the maximum level of flexibility under conditional uncertainty to make switch decisions by quantified ability manager. It implies that the option value on labour shifts is based on the increase of additional shifts and the consideration of appropriate timing to shift.

Regarding the option to switch in electricity markets, the option using on wind generation assets is affected by the switchable tariff (Yu et al., 2006). Yu et al. (2006) provide that the fixed tariff creates a higher priority to the quantity of wind generation. The time-varying and location-dependent electricity prices differ the wind energy and provide higher priority to the quality of wind generation. It implies that the switching tariff reduces the risk exposures of wind generators and creates more value to wind generators based on the flexibility of switching and accuracy of short-term forecasts.

2.7.6 Corporate Growth Options

Trigeorgis (1996, p. 12) describes that an early investment (e.g., in R&D, lease on undeveloped land or oil reserves and strategic acquisition) is a link in a chain of interrelated projects, providing the future growth opportunities. The option value of the early projects derives slightly from the expected directly measurable cash flows due to future growth opportunities (Pindyck, 1988). Corporate growth options establishing future opportunities are considerable in strategic importance (Myersn, 1977; Trigeorgis, 1988).

Chung and Charoenwong (1991) provide that certain enterprises could not take place in investment opportunities when the value of growth opportunities is recognised by future investment. It implies the value of the firm include the existing internal asset value and the value of future growth opportunities due to the corporate growth options. Kellogg and Charles (2000) provide that the high-tech biotechnology companies have a high stock price due to the products from early stages of development, although no product revenue. When applying the decision-tree method and binomial-lattice method to value the share price of high-tech companies, the real options evaluation methods reflect the early value of the high-tech companies is essential with a corporate growth option. The infrastructure and experience gained from the initial investment can address the firm at a competitive advantage, which reinforces itself if learning-cost-curve effects are present (Kim et al., 2017).

2.8 Concluding Remarks for Real Options in Real Estate Market

A literature review relevant to real options approach applied in the real estate market is presented. Several studies have provided that real options help evaluate investments in land development whenever there is uncertainty that can affect investment decisions, at the same time, there is flexibility to alter or to expand this investment (Čirjevskis and Tatevosjans, 2015; Rocha et al., 2007; Ross, 1978).

Regarding the model of land development (Equation 2.32), the increase of option premium delays the building activity, while the decrease of option premiums encourages land development. In order to successfully determine the presence of real options premium requires the predictions of underlying house prices and examinations of uncertainty about underlying house prices.

To measure the house price uncertainty, the underlying house price must be estimated firstly because the price is intangible for the future building on vacant land (Quigg, 1993). In this thesis, the spatial Durbin fixed effect model is applied to underlying house prices in order to forecast the house price within a spatial consideration. This is because spatial Durbin fixed effect model not only incorporates the SAR and the SEM in terms of the spatial lags of both the dependent variables and explanatory variables but also captures spatial heterogeneity in terms of spatially varying coefficients within region and time period specific effects. In contrast with the prior studies, the OLS estimator is applied to the underlying house prices (e.g., Capozza and Helsley, 1990; among others). The neglect of spatial lags on OLS regression leads to the unbiased results but inefficient parameter estimators and biased variance estimators.

To measure the uncertainty about underlying house prices, this thesis employs the GARCH model due to the assumption that current volatility is affected by previous innovation to volatility (Miles, 2008). The advance of the GARCH model, in the field of house prices, compared to the ARCH model is present in terms of the more restricted lag structure successfully capturing the dependencies in the conditional moments.

To investigate the relationship between the price uncertainty and timing of land development, the proportional hazard model is applicable based on the previous studies (see, for example, Cunningham, 2006, among others). However, these studies did not consider the spatial effects on land prices. Basu and Thibodeau (1998) illustrate that lack of spatial effects leads to the inefficient parameter estimators and biased variance estimators. In this thesis, the proportional hazard model incorporating spatial Durbin model is employed to examine the effects of price uncertainty on timing of land development. By this way, the transformed model not only considers the time specific fixed effects but also contains the spatial lags of land price and its explanatory variables.

In order to test the presence of real options in land markets, the effects of underlying house price and its uncertainty on land prices are examined by OLS estimator in this thesis. Referred to Equation 2.32, the uncertainty about underlying house prices increased the option premium on land providing the current (e.g., non-housing) use more valuable than immediate building activities. If there is a greater level of price uncertainty according to the economic information, then the vacant land will be traded at a premium above discounted future rents in current low capital use, $R_{current}$.

Regarding the model of real options valuation, the Black-Scholes model valuing the real options premium on vacant land overcomes the traditional capital budget. This is because the Black-Scholes model for real options have been applied to land development to account for the uncertainty based on the flexibility, volatility of uncertainty and timing of land development, where the traditional DCF is unable to do so (Tsekrekos and Kanoutos, 2013). In this thesis, the Black-Scholes model is employed to value the real options premium on vacant land.

Last but not least, this section reviews the real options approaches applied to the various sectors of the economy, such as agriculture, R&D-intensive, pharmaceuticals, natural-resource, electricity and investment appraisal, based on the categories of real options. The real options approach providing the optimal option values under the uncertainty with alterative flexibilities contributes the investment decision-making to the various industries.

Chapter 3 The Development of Housing Market in China

3.1 Introduction

The housing market in China is a significant part of the Chinese economy. In 2017, housing sales achieved 13.37 trillion RMB accounting for 16.4% of China's GDP (Liu and Xiong, 2018). China's average house prices were increasing rapidly from ¥503 in 1988 to ¥6,793 in 2015, which encourages this chapter to review the effective fundamentals and policies debates regarding the Chinese housing market in the development literature. In this chapter, Section 3.2 reviews the characteristics of the Chinese housing market. Section 3.3 demonstrates the emergence of a real estate market in China in terms of housing reform, urbanisation and circumstance of "ghost towns". In particularly, Section 3.4 highlights the implications of household behaviours on house prices in terms of income, price-to-income ratio, home size and down payments. Section 3.5 highlights the implications of land supply on house prices in terms of the fiscal revenues and debt of local government in China. Section 3.6 addresses the participatory methodologies to the house prices assessment. Section 3.7 includes a summary review of the related literature for the Chinese housing market and general discussion about the gaps existing in the current literature.

3.2 Characteristics of Chinese Housing Market

The transformation of Chinese real estate model has increased motivation to review the effective fundamentals and policy debates of house prices regarding the Chinese housing market development literature (Chen et al., 2015; Gan et al., 2010; Koss and Shi, 2018; Wang, 2011). The housing privatisation, derived from housing reform, stimulates the household's housing consumption and then increases equilibrium housing demand in China (Gan et al. 2010 and Wang, 2011).

The urbanisation simulated the demand for housing in the urban area significantly for the last three decades. The reasons are in two-fold. First, the relaxation of the Hukou system implemented population migration and raised in rural-to-urban migration and the new urban centre's development after 1978. Second, China developed 10th Five-Year Plan in 2001 which regarded the urbanisation as a national strategy to stimulate demand and encourage the housing market to be a significant factor in China's economic growth. The urbanisation rate drives up the construction of new homes. However, it is mentioned that the construction boom was caused in the Chinese housing market and was featured as a high vacancy rate in cities and then lead to “ghost towns”. Accordingly, the supply of land plays a significant role in the Chinese urbanisation process.

The housing assets accounted for 66% of household wealth in China in 2016 (Liu and Xiong, 2018). The steady growth in per capita income drives property prices up in China (Chen and Li, 2011); however, the house transaction price has been growing much faster than the average income from 1997 to 2017 (Ge and Wu, 2017). Fang et al. (2016) argue that the rapidly increasing house price in China is also contributed by the households in the low-income from purchasing houses. Liu and Xiong (2018) provide several factors that explain the willingness of low-income households to afford financial burdens of purchasing houses.

Due to the Budget Law, the Chinese local governments expend the fiscal capacity by non-budgetary funding sources such as land sales. The mixture of local government fiscal policies in China causes corruption in the Chinese land market (Cai et al., 2017 and Chen and Kung, 2018). The “Local Government Financing Platform” (LGFP) arranges contrary progress of Budget Law to constrict the budget restraint issues of local governments leads to the growth in debt by local governments (Bai et al., 2016).

In order to investigate the Chinese housing market systematically, it is essential to capture the house prices for major cities in China. The difficulty in capture a house price is present because the house price requires to compare the prices of the same houses over time. Hedonic price regression focuses on the unobserved and time-varying characteristics which result in biased estimates of the house price (Bajari et al., 2010). The IV-GMM method restricts unobserved heterogeneity and limited the consistency of the dependent variable (Baltagi, 2001).

3.3 The Emergence of a Real Estate Market in China

3.3.1 Housing Reforms

Under the centrally planned economy, urban housing belonged to a portion of the socialist welfare system was called “welfare housing” in 1978 (Chen et al. 2015). Based on this scheme, the central government assigned land to work units (Danwei in Chinese) which then developed these lands into houses that were provided to their employees.[15] Bray (2005)

[15] Central government represents the state council, ministries, and the China Banking Regulatory Commission.

describes Danwei as the working place in China.[16] Dan Wei provides employees with housing and medical supplies, which are not covered by the employee's salary (Chai, 1996). Welfare housing denoted the benefits for employees and the justice of socialism. However, equalitarian allocation was compound, and the scarcity of housing and weak housing conditions were problems (Chen et al. 2015).

Housing commercialisation and privatisation were facilitated since 1990 referred to the first national conference on the housing market which reformed the Chinese housing market for a second time.[17] Regarding the consideration on stabilisation of housing market development, the housing reform was implemented critically in step-by-step increments in China.[18] The inceptive housing reform was characterised by slight enhancement on increasing rent and improvement of housing expenditure to individual workers due to the gradual housing commercialisation (Chen et al., 2015). Market-orientated reforms were implemented to accelerate the transition of housing from a welfare provision to a commodity (Koss and Shi, 2018).[19] Regarding the diversifications from housing allocation system, the Chinese citizens were required to purchase housing on the market at the family. This situation unleashed a flood of private housing demand and prompted a significant increase in the cost of commodity residential housing in China (Chen et al., 2012).

The privatisation of housing has a significant impact on China's economy. Before the abolishment of welfare housing, more than 90% of housing investment was from central government or state-owned enterprises. In contrast, the central government investment declines to less than 50% after the privatisation of housing. The rate of privatisation for urban housing had already increased to 80% in most provinces and almost 100% in Shanghai until 2001 (Chen et al. 2011). The housing privatisation stimulates the household's housing consumption and then increases equilibrium house prices in China (Gan et al. 2010 and Wang,

[16] See Bray (2005) for social space and governance in urban china: the Danwei system from origins to reform.

[17] Before 1978, China did not have a private urban housing market. The national state owned the land use rights. In 1980, Beijing Municipal Commission of Housing and Urban-Rural Development set up the urban development plans, which began the comprehensive development of real estates.

[18] In 1981, experimental projects for the development of commercial buildings were started in Shenzhen and Guangzhou. Shenzhen was an initial pilot city of housing privatisation before applying the changes to other areas of China. In 1992, Deng Xiaoping inspected Shenzhen and found there was a significant improvement in economic conditions after housing reform. Deng Xiaoping believed that the experience of Shenzhen was worth promoting nationally. Subsequently, China's real estate development started in earnest in the coastal cities, such as Hainan, Beihai and Guangzhou. In 1994, the central government allowed state-sector employees to purchase full or partial property rights to their current apartment units at subsidised prices. In July 1998, the Chinese government announced the termination of "Welfare Housing" and the cancellation of limits for house prices (Koss and Shi, 2018).

[19] In 1980, chairman of the Chinese People's Political Consultative Conference, Deng Xiaoping, defined the house as a commodity.

2011). The dramatic transformation of housing from privatisation stimulates entrepreneurship in China by alleviating credit constraints (Wang, 2012). The housing privatisation is relative to substantial increases in income inequality in China (Novokmet et al., 2018). The abolishment of welfare housing system introduces the residential mortgage loans to the Chinese housing market and impacts on bank systems in terms of mortgage down payment and mortgage interest rates (Koss and Shi, 2018).

Therefore, the housing demand for households and enterprises have been influenced significantly due to the housing reforms and then affect the house price. In this thesis, the housing fundamentals (e.g., income, mortgage down payment rates, fiscal policy) and their influences are investigated in order to examine the house prices in the Chinese housing market.

3.3.2 Urbanisation

China's urbanisation process has experienced a meandering exploration course. In 1978, the huge population and poor agrarian economy haunted China. China implemented strict regulations on rural-to-urban migration, known as the Hukou system, to provide a stable food supply and adequate public services to urban citizens. Hukou system not only perverted China's labour market but also limited the Chinese housing market development before 1978 (Chan and Zhang, 1999).

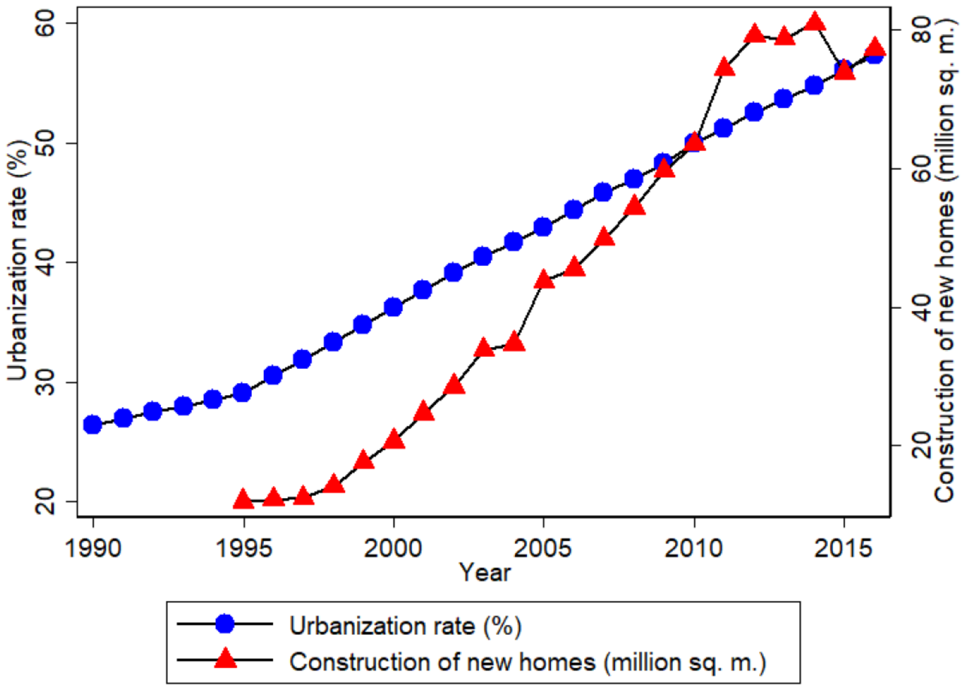
The relaxation of the Hukou system implemented population migration and raised in rural-to-urban migration and the new urban centre's development after 1978. The population migration is mentioned by the previous studies which are the migration pattern leading to the new urban centres (Ma, 2002, 2003). Chen et al. (2011) mentioned that the most migration from countryside to city is unofficial migration without Hukou transfer before 2001, although population migration in China is regulated as official migration.[20] They suggest that urban housing growth is based on not only the rapid Chinese urbanisation but also the massive migration with the transfer of household registration (floating population).[21] The floating population mainly results in prosperous housing demand in the urban area. It is recommended that the official urbanisation data in China has a lower level than that in a realisation.

[20] The official migration is with Hukou transfer (or permanent migration) and unofficial migration is without Hukou transfer (or temporary migration) (Chen et al. 2011).

[21] Migrants without the official transfer of household registration are called the floating population, or temporary migrants, and are usually excluded from urban population statistics (Chen et al. 2011).

China developed 10th Five-Year Plan in 2001 which regarded the urbanisation as a national strategy to stimulate demand and encourage the housing market to be a significant factor of China's economic growth. In terms of cooperating this strategy, the State Council issued a policy that allowed free rural-to-urban migration for counties and small towns and completely abolished urban-to-rural divide in Hukou system in 2014. Chinese citizens are unlimited to urban areas, except several Tier 1 cities such as Beijing and Shanghai. The growth in the urbanisation rate from 1990 to 2016 is provided in Figure 3.1. The urbanisation growing in a stabilisation simulated the demand for housing in the urban area significant. The urbanisation process accounts for about 80% of the growth in China's urban house prices (Garriga et al., 2017). Therefore, it is recommended that the urbanisation process influence urban house prices significantly. The variations in the number of births over time result in large and predictable changes in the demand for housing (Mankiw and Weil, 1989). Due to the Chinese large population base, the high urbanisation rate represents the essential demand for housing in the urban area and then influences the urban house prices significantly.

Figure 3.1 China's Urbanisation Process



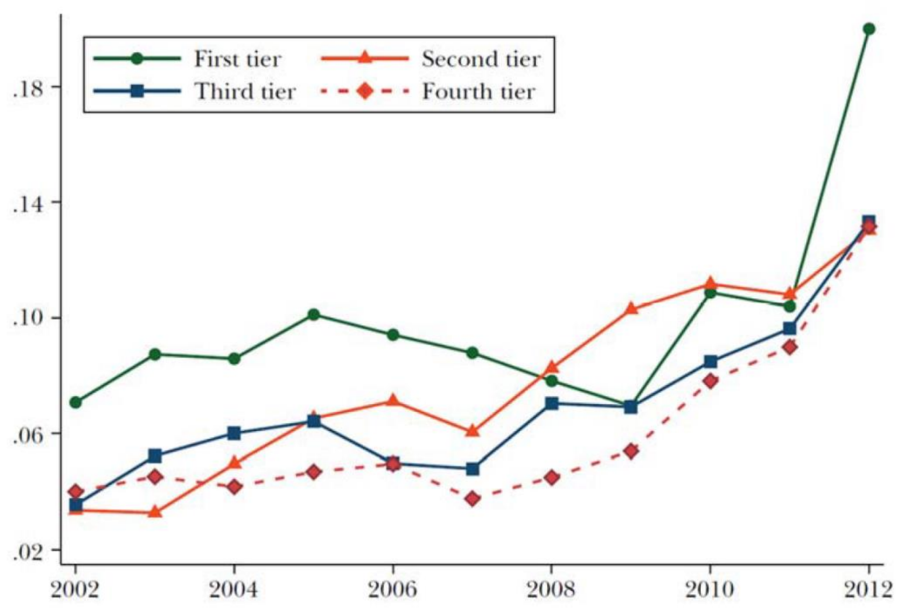
Source: Liu and Xiong (2018)

Urbanisation is still going on in China. By 2016, there are more than 40% of Chinese citizens living in rural areas (Liu and Xiong, 2018). The completion of new homes achieved a balanced point compared to growth in the urbanisation rate in 2011 (Figure 3.1). Construction of new homes exceeded urbanisation rate after 2012 and declined in 2015, indicating a slowdown in the construction boom. In other words, in the Chinese property market, insufficient supplies coexist with steady increases in urbanisation rate between 1990 and 2011; and the construction boom exists between 2011 and 2015. Essentially, it implies that the urbanisation rate drives up the construction of new homes between 1990 and 2011; however, it is mentioned that construction boom may feature a high vacancy rate in cities and then lead to a housing bubble. Accordingly, the supply of land plays a significant role in the Chinese urbanisation process. In this thesis, the supply of land and population are involved in the models in order to examine the relationships between house prices and them.

3.3.3 Ghost Towns

The "ghost towns" could be found mostly in empty urban districts with newly constructed in areas far away from the central business district (CBD). The noted cases contain Ordos in Inner Mongolia and Zhengdong New District in Henan Province. In other words, China's real estate market features a high vacancy rate in cities (Liu and Xiong, 2018). Glaeser et al. (2017) provide that the housing vacancy rate increased rapidly after 2009 across Tier 1 to 4 cities (Figure 3.2). Therefore, it is recommended to explore whether the "ghost towns" caused the housing bubbles in China and the effects of "ghost towns".

Figure 3.2 Vacancy Rates for Chinese Cities, 2001-2012



Source: Glaeser et al. (2017)

A high vacancy rate is an essential indicator of a housing bubble (Glaeser et al., 2017). Liu and Xiong (2018) explain the process of the high vacancy rate in China's housing market which is occurred by the low occupancy rate of completed residential properties and the long duration of an occupied new district. They also provide that the influencing factors of the process are land sale revenue and the outflow of residents to Tier 1 and 2 cities for the lower Tiers cities. Zhang, Jia, and Yang (2016) consider high vacancy rates in China's cities have increased income inequality, measured by the income GINI index. Anglin et al. (2014) and Wang et al. (2018) illustrated that the local government officials, China's land leasehold system and fiscal system are the essential factors for the high vacancy rate in China. Thus, the rapid development of housing in China is at a crossroads. It implies that it is valuable to evaluate what are the main economic fundamentals influenced by the real estate boom and then how to balance these fundamentals in order to achieve a relatively balanced economic condition.

3.4 Housing market and Households

3.4.1 Household Income and Price-to-Income Ratio

Housing assets have been a significant part of household wealth in China. The housing assets accounted for 66% of household wealth in China in 2016 (Liu and Xiong, 2018). Household demand is an essential factor in the Chinese housing market fundamentals and is mentioned by enormous academic literature. Wang and Zhang (2014) illustrate that the citizen income, urban population, urban land supply and construction costs are significant fundamentals in the Chinese housing market. Chen and Li (2011) find that housing-price growth is closely related to demand-side variables, such as increases in household income, employing national and province-level panel data. Thus, it is valuable to investigate the household income in China in terms of the contributions and effects on the housing demand.

Most studies suggest that the relationship between income and house price is positive in China (Chen and Li, 2011; Fang et al., 2016; Hillebrand and Kikuchi, 2015; Kim, 2018). Fang et al. (2016) argue that the rapidly growing house price in China is also contributed by the households in the low-income from purchasing houses. Figure 3.3 provides the time series of the household income of p10 and p50 for first-, second-, and third-tier cities.[22] The

[22] Percentile ratios - an alternative way of looking at inequality is to compare incomes at different points along the income distribution (e.g., how much more income is received by those near the top compared with people at

household incomes of mortgage borrowers with p10 and p50 increase in a stabilisation across the three tiers of cities. This growth is in line with the income growth of the overall urban citizens (Per Capita GDP in Table 3.1). The relatively wealthy of the citizens represent the median-income p50. The low-income households, p10, represents the 25th percentile of the citizens in Tier 1 cities and the 30th percentile in Tier 2 cities. It implies that mortgage borrowers come from not only top-income households but also low-income. The house purchasing power in the Chinese housing market is influenced by not only the household with high-level incomes but also the household with low-level incomes. Therefore, the price-to-income ratio is applicable to analyse the housing demand in the Chinese housing market because it represents a measure of the financial burdens for the households who are purchasing a home (Zhang, 2015).

The steady growth in per capita income drives property prices up in China; however, the house transaction price has been growing much faster than the average income from 1997 to 2017 (Ge and Wu, 2017). Shen and Liu (2004) provide per capita disposable income significantly influence about 60% of the house price in China with panel data on 14 cities in China from 1995 to 2002. Fang et al. (2016) provide that the price-to-income ratios for the low-income household group are above 8 in the three tiers cities in 2003, particularly a peak of 10.7 in 2011 in Tier 1 cities. The price-to-income ratio for the middle-income group has an analogous pattern over time across the three tiers cities, which performs around 6 in 2003 to a peak of around 8 in 2011 and then decreases to around 6.6 in 2012. It indicates that the house price and housing affordability is inequality in China. In other words, the financial burdens affordability of household in China is unequal to the distribution of individual wealth. The willingness of low-income households affording the financial burden of buying homes should be mentioned for housing demand.

Liu and Xiong (2018) argue that the consumption motives cannot represent the willingness of low-income households to afford financial burdens of purchasing houses. Regarding their suggestions, renting homes is significantly cheaper than buying homes in terms of the rental yields of housing in Tier 1 cities are lower than the yield of China's one-year Treasury bonds in July 2018. Liu and Xiong (2018) provide several factors that explain the willingness of low-income households to afford financial burdens of purchasing houses. First, the Chinese

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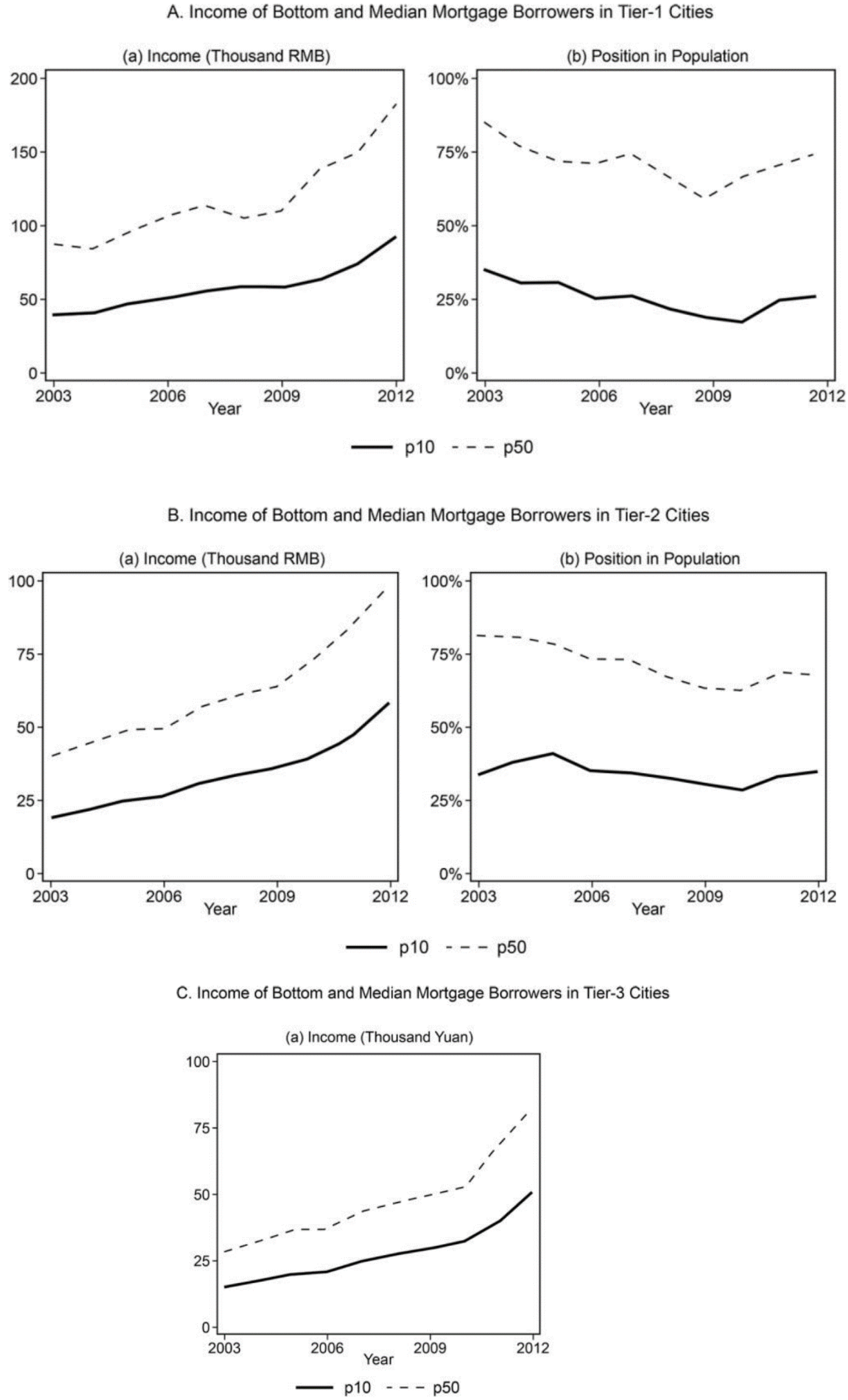
the middle or the low). The p90/p10 ratio means someone at the 90th percentile had a household income under four times larger than someone at the 10th percentile. Similarly, the p90/p50 ratio compares the 90th percentile with the 50th percentile (i.e. the median). The p50/p10 ratio compares the median with the 10th percentile (McGuinness and Harari, 2019).

Figure 3.3 Annual Income of Mortgage Borrower



Source: Fang et al. (2016)

Table 3.1 GDP and Average House Price in China

	GDP (100 million yuan)	Per Capita GDP (yuan)	House Price (yuan/sq m)	House Price Change (%)	House Price Index
1987	12174.6	1123	408	0	100
1988	15180.4	1378	503	23.3	123.3
1989	17179.7	1536	573	13.9	140.4
1990	18872.9	1663	703	22.7	172.3
1991	22005.6	1912	786	11.8	192.6
1992	27194.5	2334	995	26.5	243.9
1993	35673.2	3027	1291	29.8	316.4
1994	48637.5	4081	1409	9.1	345.3
1995	61339.9	5091	1591	12.9	389.9
1996	71813.6	5898	1806	13.5	442.6
1997	79715	6481	1997	10.6	489.5
1998	85195.5	6860	2063	3.3	505.6
1999	90564.4	7229	2053	-0.1	503.2
2000	100280.1	7942	2058	0.2	504.4
2001	110863.1	8717	2170	5.4	531.9
2002	121717.4	9506	2250	3.7	551.5
2003	137422	10666	2359	4.8	578.2
2004	161840.2	12487	2714	15	665.2
2005	187318.9	14368	3167	16.7	776.2
2006	219438.5	16738	3367	6.3	825.2
2007	270232.3	20505	3864	14.8	947
2008	319515.5	24121	3800	-1.6	931.4
2009	349081.4	26222	4681	23.2	1147.3
2010	413030.3	30876	5032	7.5	1233.3
2011	489300.6	36403	5377	6.8	1317.9
2012	540367.4	40007	5791	7.7	1419.4
2013	595244.4	43852	6237	7.7	1528.7
2014	643974	47203	6323	1.38	1549.8
2015	689052.1	50251	6793	7.43	1665

Source: National Bureau of Statistics of China households have a higher saving rate relative to developed countries because the ratio of aggregate savings by households and firms stands the national GDP by 35% in the 1980s and gradually increased to over 50% in the 2000s (Fang et al., 2016). Second, the few investment assets for households and firms to invest the savings referred to the Chinese relatively underdeveloped financial markets. The central government implements the severe capital regulation which forbids investing the savings into global financial markets, which encourages housing to be the investment assets instead of consumer products. Third, the largely unbalanced gender ratio in China represents that male confronts competition in the marriage market. As homeownership is treated as an important status symbol, the competition in the marriage market gains the demand for housing (Wei et al., 2012).

In this thesis, household income is treated as an important fundamental to the house price based on the above arguments. Thus, the GMM model is employed to examine the endogenous influences of household income on house prices in the Chinese housing market.

3.4.2 Home Size

Home size is significant on the consumption value of a home. Fang et al. (2016) provide that despite the critical financial burdens afforded by the households, the home size is spacious which is more than the standards of most metropolitan areas in the world such as London, Hong Kong, Singapore, New York and Tokyo. The low -income borrowers in Tier 1 cities, which house prices are the highest in the Chinese housing market, purchased the smallest homes. The average home size of the low-income mortgage borrowers in Tier 1 cities is in a range between 71 and 81 square meters between 2005 and 2015. For a family of three people (a couple with one child based on the Chinese birth control policy), the home size for per person is about 25 square meters (Fang et al., 2016). Though low-income borrowers in Tier 1 cities own the smallest home sizes in China, these home sizes are even more than standards of most metropolitan areas. Thus, home size in China influences the housing demand in terms of China’s characterised consumer behaviour of households. In this thesis, the hedonic model is employed to examine the relationship between house prices and house characteristics.

3.4.3 Mortgage Down Payment

In the Chinese housing market, the mortgage down payment, imposed by the People's Bank of China (PBC), plays an essential role to regulate the real estate market conditions by the Chinese government. Mortgage down payment is a significant fundamental preventing bank against defaulting on the loans when the future housing market is unfavourable (Benito, 2006). In China, the high levels of down payment represent the strict mortgage policies on banks implemented by PBC.[23] Fang et al. (2016) provide that down payment rates in the mortgage are above 30% in most cities of China between 2013 and 2012. The average down payment ratio divided into income levels demonstrates that the lowest income-level borrowers are more than middle-quintile income level borrowers in Tier 1 and Tier 2 cities. The house price is restrained influenced by the high-level down payments referred to the previous studies. For example, Yu (2010) applied panel data econometrics to achieve the conclusion that the mortgage down payment has a negative effect on house prices from 1998 to 2007. Li and Chand (2013) employ annual data with 29 provinces of China from 1998 to 2009 and provide that the mortgage down payment influence China's urban house prices by about 0.5% negatively. The high levels of down payments in China not only reduced the risk of household default for the bank but also declined the housing demand significantly.

The Chinese high-levels of mortgage down payment are in contrast to the zero down payment and negative amortisation mortgage in the US during the housing bubble between 2003 and 2006. Mayer et al. (2009) demonstrate that the subprime households are generally provided by down payment between zero and 5% in terms of the home purchases financing in the US. The negative amortizations are accepted in several mortgages. These borrowers tend to default on their mortgage loans aggravating the US housing market decline when the US house prices decrease after 2006. However, the Chinese high levels of down payments (e.g., 30% of total payments) prevent banks against defaulting on the loans when the future housing

[23] In June 2003, the Chinese government implemented "121st policy", which controlled banks with real estate development loans, land loans and personal housing loans. The down payment for householders purchasing the second house was increased. At the end of 2003, the "18th policy" relaxed the banks. The mortgage down payment for household purchasing second house was decreased. In 2007, the "Notice on Strengthening Commercial Real Estate Credit Management" specified the mortgage down payment could not less than 40% of the property. The mortgage down payment rates increased by 1.1 times. The policy also stated that projects, for which the capital raised does not reach 35% of the total cost, are not eligible for a loan. In 2009, the Chinese government issued a package of economic stimulus programs with ¥4 trillion in capital to stimulate the supply of houses. The mortgage down payment rate on houses was reduced to 20%. In 2010, the "10th policy" stipulated that the mortgage down payment increased from 20% to 30%. The mortgage down payment for second-house buyers were not allowed to be less than 50%. In early 2013, the General Office of the State Council released national policy known as the "National 5", which is "Notice on Further Improving Regulations of the Real Estate Market" by requiring high down payment rate (first home 30% and second home 70%) (Sohu, 2017).

market is unfavourable. It implies that the Chinese mortgage borrowers will not tend to default on the loans excepting that there is a 30% decrease in the house prices of China. Additionally, the mortgage loans in China resembles recourse loans which warrant a right for lenders to withdraw other real assets from the borrowers in terms of mortgage defaults. China reduces the risk of subprime credit crisis which resembles the US housing bubbles.

In this thesis, mortgage down payment is regarded as an important fundamental to the house price based on the above arguments. The endogenous influences of mortgage down payment on house prices in the Chinese housing market are examined by the GMM model.

3.5 Land Sales and Debt of Local Governments

Land sale revenues represent a significant contribution to the local governments' budgets in China (Fang et al. 2016). In 1994, the fiscal reform, known as Tax-sharing Reform, regulates that the central government substitutes local governments as its tax agencies in order to reallocate tax revenues to the less developed areas.[24] The transformation of fiscal incentives may occur a shift of local governments that developing industry of "urbanising" (e.g., develop the real estate and construction sector; Kung et al., 2009). Due to the Budget Law, local governments expend the fiscal capacity by non-budgetary funding sources such as land sales.[25] Fang et al. (2016) provide the share of land revenues in city fiscal budgets is 68% in 2003, 42% in 2008 and 70% in 2010 and 2011, respectively, at the national level. Regarding the budgetary deficits, land is sold for free or at a discount to firms who has potential projects in the cities and support local industrial policies. The mixture of local government fiscal policies in local housing markets implies that the financial distress of local governments and defaults by local governments may occur due to the decline in land or house prices. However, the Budget Law increases the supply for land to a certain extent to the Chinese housing market.

Fang et al. (2016) provide that the belief of households contributes the increased Chinese housing demand within the last decade. Due to the mixture of local government fiscal policies with local housing markets, enormous households consider the housing market will

[24] The local governments are forbidden to levy local income taxes, property taxes, or sales taxes, which are essential revenues for local government in western countries. Whilst the local governments in China are interrupted by issuing debt to obtain capital projects (Han and Kun, 2015).

[25] In 1995, the Chinese government enacts Budget Law in that enable the local governments to obtain external financing or operate budgetary deficits (Fang et al. 2016).

not be unfavourable because the central government will be encouraged to implement policies to develop the housing market. The households' reliance on local governments on land-sales revenue for the fiscal budgets influence the Chinese housing market and then increase the house price.

Many previous studies illustrate that the mixture of local government fiscal policies in China causes the corruption in the Chinese land market (Cai et al., 2013; Chen and Kung, 2016; Cai et al., 2017; and Chen and Kung, 2018). In terms of this situation, the central government enacted the statutes that the lowest price for industrial land and investment intensity for the alternative cities and counties referred to the development levels and geographic locations. In 2012, the regulation enacted the statutes that the leasehold sales for commercial and residential developments apply the open auctions.[26] The land transactions, which employed open auctions, increase from less than 20% in 2000 to over 90% in 2012 (Liu and Xiong, 2018). This regulation not only adjusts the land market chaos but also provides an adequate supply of land.

Land sales revenues are regarded as significant collaterals for local governments to increase debt financing in China (Liu and Xiong, 2018). In 2009, the Chinese government issued a package of economic stimulus programs with 4 trillion RMB in capital, which is equivalent to 12.5% of GDP in China, to stimulate mostly infrastructure projects in order to prevent the spill-over effects of the world financial crisis. The central government enables local governments to implement the "Local Government Financing Platform" (LGFP) to increase debt because it is inaccessible for local government to regular land sales within a short period.[27] The LGFP arranges contrary progress of Budget Law to constrict the budget restraint issues of local governments leads to the growth in debt by local governments (Bai et al., 2016). When the central government tightens monetary policy to limit debt accumulation by local governments, LGFP has been regulated.

In this thesis, the fiscal measures and monetary policy instruments are treated as instruments of mortgage down payment. This is because they influence the Chinese house price indirectly through the loan of the bank system based on the above literature reviews.

[26] Regulation represents the No. 11 regulation "Regulation on the Transaction Method of Leasehold Sale of Land by Local Government," issued by the Ministry of Land and Resource.

[27] "In a typical arrangement to support a certain infrastructure project, a local government creates an LGFP and injects land reserves or future land sale revenues as capital into the LGFP, which in turn can apply for bank loans" (Liu and Xiong, 2018).

3.6 Examining House Prices in China

In order to investigate the Chinese housing market systematically, it is essential to capture the house price for major cities in China. The difficulty in capture a house price increases because the house price requires to compare the prices of the same houses over time. This problem is more severe in emerging housing markets than that in mature markets because of the alternative characteristics of house and time-varying buildings (Fang et al., 2016).

Hedonic price model is applicable to value the house price based on the hypothesis that goods are valuable due to their utility characteristics and determination of a set of choices made by consumers and producers under market clearing conditions. Rosen (1974), who factor consumer behaviour into a hedonic regression, establishes the relationship between the product's price and its attributes. In practice, the regression coefficients are generally regarded as implicit or "hedonic" prices (Bajari et al., 2010). The hedonic price model can be expressed as:

$$P = \alpha + \beta X + \varepsilon \tag{3.1}$$

where P is the price of goods. X represents a vector of goods attributes. β represents a vector of the attributes coefficients. ε is an error term.

The implicit price can be described as the additional value of a product when individual attributes are increased while all other attributes remain fixed. The estimate of implicit prices proposes that the consumer's willingness to pay for a small alteration in a particular attribute is marginal. "These implicit prices can be used to recover marginal willingness to pay functions for use in valuing larger changes in attributes" (Bajari et al., 2010). The accuracy of hedonic price regression depends on the data characteristics and qualities. The advantages of hedonic price regression focus on the unobserved and time-varying characteristics which result in biased estimates of the price.

The hedonic pricing model is appropriate for the capture of the house price. In the housing market, house is a commodity with attributes due to its characteristics, such as size, floor level, number of rooms and orientation. However, the hedonic pricing model ignores the consideration of economic fundamental effects on house prices. In this thesis, we incorporate economic fundamentals into the hedonic pricing model in order to examine the house price not only individually but also macro-economically.

Baltagi (2001) argues that employing the values of the other variable regressors as instruments can increase consistency and efficiency of the model. The generalised method of moments with instrumental variables (IV-GMM) method restricts unobserved heterogeneity and limited the consistency of the dependent variable. The IV-GMM method can be specified as:

$$P_{it} = \alpha_0 + \gamma X'_{it} + \sum_{i=1}^{n} \lambda_i Z_i + \varepsilon_{it} \tag{3.2}$$

$$X'_{it} = [y'_{2i} \; x'_{1i}] \tag{3.3}$$

$$z'_i = [x'_{1i} \; x'_{2i}] \tag{3.4}$$

where i denotes an individual property. t represents the date of property transacted. P_{it} is the house price. X'_{it} combines endogenous variables and exogenous variables and the dependent variable is denoted by y rather than y_1. Z_i is used as a vector representing the control variables, λ_i is an estimated coefficient for control variables, and ε_{it} is the random error.

The Hausman tests are applicated to explore the presence of endogenous variables. The Sargan test of the instrumental variables is implemented to illustrate whether the instrumental variables are relative to the error of regression. The first-stage test of GMM aims to test whether the instrumental variables are relative to endogenous variables. Regarding the complex relationship between housing fundamentals, economic fundamentals and financial fundamentals in the Chinese housing market the combination of the hedonic pricing model and IV-GMM method is an appropriate econometric technique for achieving the investigation of the determinants of house prices.

3.7 Conclusion

The housing market has a significant impact on the Chinese economy. The dramatic transformation of housing from state-owned to private stimulates the demand for housing in terms of consumption of households and investment on housing by enterprises (Chen et al., 2015; Gan et al. 2010; Koss and Shi, 2018; Wang, 2011, 2012). The housing commercialisation influences the supply for land in terms of fiscal reforms (e.g., tax-sharing reform and budget law) and LGFP (Bai et al. 2016; Fang et al., 2016; Liu and Xiong, 2018). In other words, the real estate assets contribute to the wealth of households for housing demand and provide the essential platform of local governments and enterprises to increase debt financing for land supply. The housing market in China is treated as an essential part of

China's financial market due to the resource loans are associated with real estate directly and indirectly.

The literature review of development in the Chinese housing market has shown that, despite the demand for housing is stimulated by consumption of households and the supply for land is illustrated by fiscal reforms, there are still different areas of contention regarding both the theoretical correctness and fundamental implications related to the house prices in China as followings.

First, the discussions of demands for households have gradually narrowed the levels of investigation to individual households. However, there are still several gaps in terms of house characteristics, such as directions of house facing (orientation), floor level of house or endogenous variables of house characteristics; also, in terms of income, such as endogenous variables of income (e.g., mortgage, CPI, interest rate, unemployment). Regarding the supply for land, although the influences of land reforms are mentioned, there are still the open debates in terms of recent fiscal changes, such as tax; in terms of the relationship between local government fiscals and bank system, such as endogenous variables of housing completed permissions and endogenous variables of the mortgage.

Second, consolidating these factors into a theoretical framework has been attended to be challenging because of the endogenous fundamentals upon which different house characteristics, household income, local government fiscals and bank system in the Chinese housing market are evaluated. The hedonic model emphasises house characteristics embedded in tradition and culture that not only establishes the relationship between the house prices and house characteristics but also focus on time-varying characteristics resulting in biased estimates of the house price (Rosen, 1973). Employing the values of the other variable regressors as instruments can increase the consistency and efficiency of the model (Baltagi, 2001). The generalised method of moments (GMM) method accounts for endogeneity by using alternative independent variables that are suspected of suffering from endogeneity. The IV-GMM method restricts unobserved heterogeneity and limited the consistency of the dependent variable. Regarding the complex relationship between housing fundamentals, economic fundamentals and financial fundamentals, the combination of the hedonic pricing model and IV-GMM method is an appropriate econometric technique for achieving the investigation of the determinants of house prices.

Third, the scarcity of theories has generated a challenge to assess the enquiry of house prices in the Chinese housing market and the use for the purposes of investments, in terms of the mixture of consumer behaviour theory, economic theory and financial theory. [28] The application of enormous theories and measures of house prices, hence, tends to the risk of infiltrating into significant conflict reasoning issues.

Fourth, studies regarding the house characteristics, consumer behaviour of households, local government fiscals, bank systems of house price for investment purposes, particularly following empirical frameworks, have yet to be fully qualified in terms of the influencing factors in the Chinese real estate market. In this respect, significant fundamentals in discussion, such as the relationship between house price and house orientation, the effects of house condition on house price, the indirect impacts of fiscal measures on house price and the relationships between consumer behaviour of households, local government fiscals and bank systems, are still limited in empirical literature on the Chinese housing market, including the emerging related studies on Zhang and Yi (2017).

[28] For example, consumer behaviour theory due to the consumer's willingness to pay for a small alteration in a particular attribute is marginal. Economic theory due to an individual property transaction is dominated by what the investor believes will happen to the market in the future without regarding any possible distortions. Financial theory due to when the money supply increases, the price of goods turns upwards, referred to the decreasing value of the currency.

Chapter 4 An Empirical Analysis of the Effect of Housing Characteristics on Property Price in Beijing

4.1 Introduction

There is a concern that the transformation of Chinese real estate model has increased motivation for rapid increasing house prices in the whole country, especially in Tier 1 cities. The housing privatisation stimulates the household's housing consumption and then increases equilibrium housing demand in China (Wang, 2011). Regarding the diversifications from housing allocation system, the Chinese citizens were required to purchase housing on the market at the family. This situation unleashed a flood of private housing demand and prompted a significant increase in the cost of commodity residential housing in China (Chen et al., 2012). The adjustment of house price due to two major reasons, which are the value of the attribute from the house itself and the factors from the external influences (e.g., economic factors or regional identities; Fang et al., 2016). The house attribute can be regarded as the house characteristics, which has the implicit value (Rosen, 1974). It is evident that house chrematistics importance of house price has attracted attention from researchers (Bajari et al., 2012; Jim and Chen, 2009; Malpezzi, 2002; Rosen, 1974; Wong et al., 2005). The essentials of economic factors influencing house prices are illustrated by the previous studies (Capozza et al., 2004; Kohn and Bryant, 2010; Riddel, 2011; Shiller, 2007).

Rosen (1974), who factor consumer behaviour into a hedonic regression, establishes the relationship between the product's price and its attributes. In practice, the regression coefficients are generally regarded as implicit or "hedonic" prices (Bajari et al., 2010). The implicit price can be described as the additional value of a product when individual attributes are increased while all other attributes remain fixed. For instance, in the Chinese land market, the land with water facility is more expensive than that of without water facility, when the other attributes remain the same, such as size and other facilities. This is because the land with water facility has a particular attribute, which is the additional value of this land. Rosen (1974) established the hedonic regression to provide the house price based on utility-maximising behaviour. The estimate of implicit prices proposes that the consumer's willingness to pay for a small alteration in a particular attribute is marginal. Moreover, "these implicit prices can be used to recover marginal willingness to pay functions for use in valuing larger changes in attributes" (Bajari et al., 2010).

As previously discussed above, the house characteristics have to be provided as much detailed as possible in order to accurately estimate the implicit values of the house. However, it is uncertain whether there are 'omitted variables' leading to biased estimates of the implicit prices. When applied to real data, several 'omitted house characteristics variables' seem to be significant in the theoretical models. Jim and Chen (2009) suggested that daylight and views from houses are significant factors affecting house prices. The previous studies (e.g., Chen et al., 2012 and Fang et al., 2016) ignore the condition of the room, which also can be the endogenous variables of house prices. This investigation tests these endogenous variables through the numbers of rooms with orientations, including room conditions that proxy daylight and natural ventilation in order to contribute the previous studies in term of introducing new flat-related factors that affect house prices.

House property had been regarded as a primary source of investment for individuals in China, which allows the investors to achieve potential profit with speculative and alternative incomes. This situation provides maximum stimulation to encourage investors to make a decision on their own deal. An individual property transaction is dominated by what the investor believes will happen to the market in the future without regard to any possible distortions (Cheng et al., 2014). Based on the theory of 'distortions beliefs' (Cheng et al., 2014), the investors ignored the risk of low demand, referred to income, may have fostered the financial circumstances that enabled property prices to rise alongside credit expansion, and subsequently spark the crisis (Gennaioli et al., 2013). Though the theory of 'distortions beliefs' illustrates the irrational increase of Chinese house prices, another reason of irrational house price can be also attributed to this. Naylor (1967) illustrates that the fiscal policy influences the housing demand indirectly. The increasing tax rates reduce the aggregate demand for GDP; subsequently, the changes in aggregate demand for GDP will indirectly influence housing demand by the diversities of intermediate economic factors, such as income, employment and prices (Naylor, 1967). In other words, the endogenous variables for housing demand influence house prices directly. Naylor (1967) also provides that an increase of investment in fixed assets will lead to a rise in GDP so that increase the prices of goods.

To date, there is a substantial literature on the influencing economic factors to house prices, for example, income (Capozza et al., 2004; Riddel, 2011; Hui and Gu, 2009; Milne, 1991; Chen and Patel, 1998), mortgage payments (Kohn and Bryant, 2010; Lee, 1997; Mints, 2007, 2008), inflation (Irving, 1911), fiscal policy (Naylor, 1967), housing starts (Maisel, 1963). However, the endogenous variables of housing demand are not mentioned in the previous studies. The method of defining the housing demand is not unique. In this investigation, the housing demand is identified by housing starts multiple floor level of the house. According to (Maisel, 1963) housing starts is a potential standard which decides the final housing demand in terms of 'a theory of fluctuation in residential construction starts'. Whereas the housing starts is the size of building permission, the investigation improved the housing demand factor in terms of relating to floor level, which makes housing demand into underlying units. Findings of this investigation suggests there is an inverse U-shape relationship between housing demand and house prices, which is consistent with the theory of 'conventional wisdom' (Galbraith, 1958). This research also tests the endogenous economic fundamentals for house price in order to explore the economic variables influencing house price indirectly. This research regards the housing demand and mortgage payment rates as endogenous variables referred to the previous studies and Chinese government monetary policies. To do this, the previous model is improved by taken account into instrumental variables.

This study overcomes the previous studies in terms of the introduction of new flat-related variables. Compared with the previous studies (Rosen, 1974; Bajari et al., 2010), the flat-related factors, such as directions of house facing (orientation) and square of floor level (FR^2) are never found. Without these factors, the implicit house price could be biased estimated. The essential finding of these new flat-related factors provides there is an inverse U-shape relationship between floor level and house prices. This investigation illustrated house orientation influences the condition of the bedroom and the condition of living room significantly and indirectly affects the house price in IV-GMM analyses, which improved the theoretical standpoint to understand the relationship between house characteristics and house prices.

In addition to the above, previous economic research has considered the variable of house demand that was designed primarily to determine the house prices. Based on the economic theory of supply and demand, excessive demand encourages the investor to have more confidence in investing in the property so that this increases the house prices (Rosenthal et al., 1991). Previous studies have found that the income elasticity of demand for housing is well below one (Rosen, 1974; Hoyt and Rosenthal, 1990; Rosenthal et al., 1991; Glaeser et al., 2008; Carrillo et al., 2014). In contrast, the present investigation applies housing starts multiple by floor level (HPP*FR) as property demand. This is because to housing starts is a potential standard which decides the final housing demand (Maisel, 1963) in terms of 'a theory of fluctuation in residential construction starts'. Moreover, this investigation employed the IV-GMM model to test the endogeneity of housing demand to the property prices respected to the instrumental variables with investment in fixed assets and local governments general budgetary revenue. This approach provides the determination of demand for houses be flexible with the economic conditions.

The application of panel analysis (i.e. fixed effects and random effects) extends the current literature by taking into account endogeneity in the IV-GMM framework with instrumental variables. In this regard, this investigation conceptually resembles and Bajari et al., (2012), who investigate property prices the role of air pollution with hedonic regression. Empirical testing of the aforementioned issues provides a valuable tool for regulators in the Beijing area, because, to the best of our knowledge, it is the first study of its kind that examines all the above; it can also be useful for regulators in other industries, such as banking and insurance. In this study, the assessment and remediation of house price will depend on the understanding of their influencing factors.

In an attempt to fill the gaps from previous studies, this investigation extends previous research in terms of the data sample. This investigation examines an extended period (2002-2014), which provides a sample with the advantage of 17,143 transacted property records with detailed information, from the Beijing core real estate area. We linked transacted property records with property addresses to track the regional effects. Key in this research is the possibility – hitherto empirically unaccounted for by the previous studies – that influencing factors that affect property prices performance include factors ignored in previous studies such as floor level of property and orientation of property. In this regard, our study conceptually resembles (Bajari et al., 2012), who investigate within property prices with hedonic regression and the role of air pollution. Empirical testing of the aforementioned issues provides a valuable tool for regulators in the Beijing area, because it is the first study of its kind, to the best of our knowledge, that examines all the above; it can also be useful for regulators in other industries, such as banking and insurance. In this study, the assessment and remediation of house prices will depend on the understanding of their influencing factors.

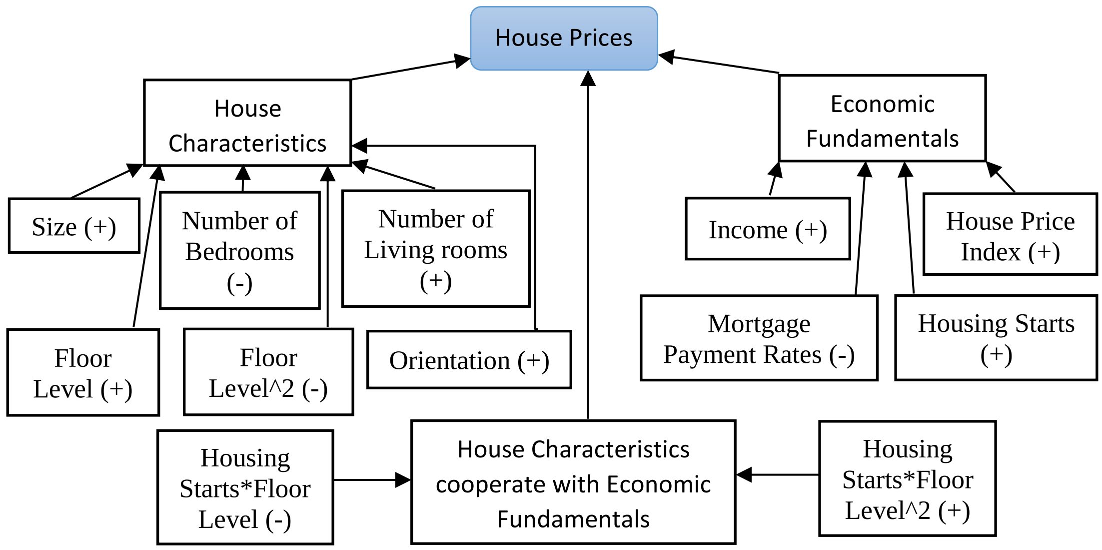
4.1.2 Research Objectives

The main purpose of this chapter is to evaluate the determinants of property price with house characteristics and economic fundamentals in seven districts of Beijing, China between 2002 and 2014. This investigation has three main objectives. First to provide quantitative analysis of house transactions to examine whether the house characteristics and economic fundamentals influence the house prices significantly. Second to investigate whether there are omitted variables that lead to biased estimates of the implicit house prices. Third to explore whether endogenous economic fundamentals and house characteristics variables are leading to biased estimates of house prices.

4.1.3 Summary of Findings and Contributions

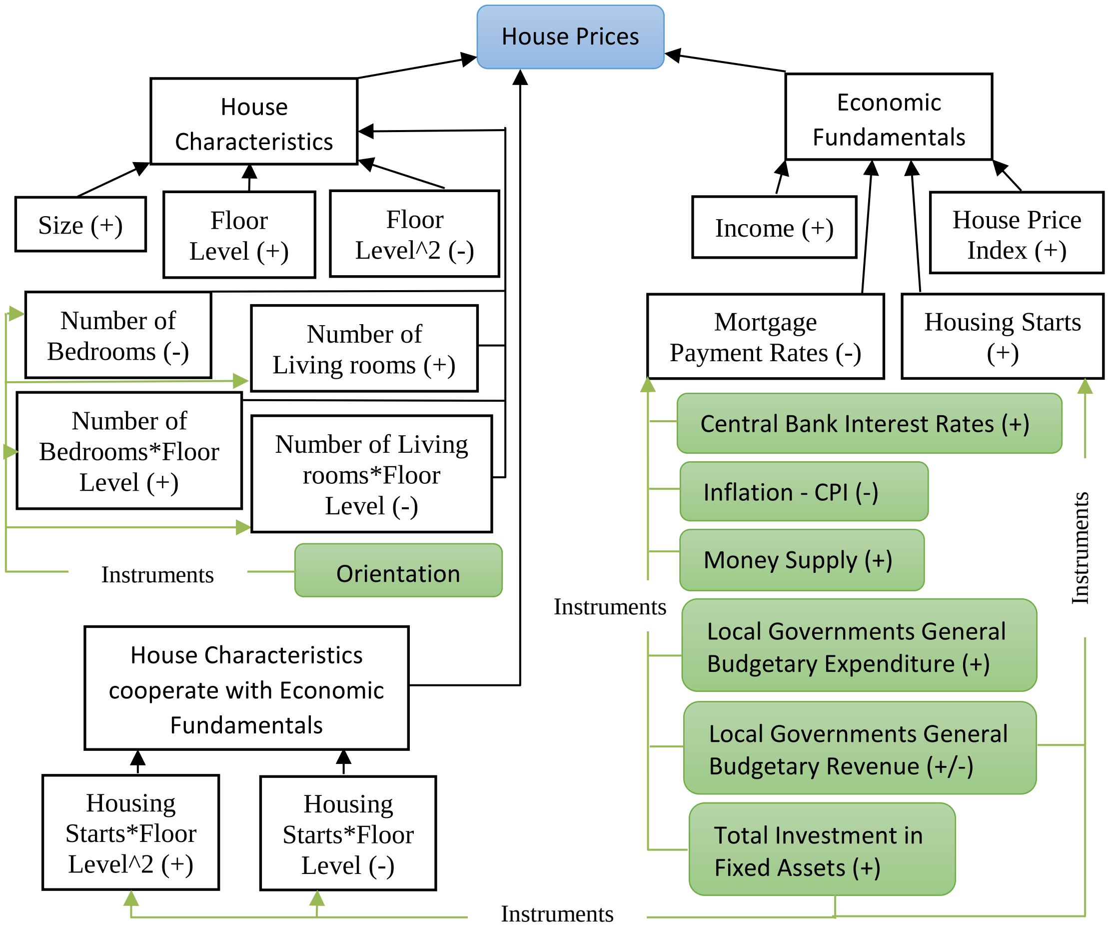
Regarding Figure 4.1, the results indicate that economic factors have influenced the property price based on the economic theories (Cheng et al., 2014; Maisel, 1963). The mortgage down payment rates influence house prices negatively and significantly referring to economic fundamentals which is in line with Yu (2010) and Li and Chand (2013). This result implies that the policy of mortgage down payments is efficient to restrain the rapid growth of house prices. If the housing market investors persistent in buying houses, ignoring the high degree of mortgage down payment rates, would causes housing bubbles. This shows consistent finding with Cheng et al. (2014) in terms of ‘distortions beliefs’. The House Price Index has a positive influence on property prices. This indicates that the general directions of housing market tend to be good, increasing the confidence of investors. The findings also provide that the increasing average income rise property prices which is in line with Fang et al. (2016) and Hui and Gu (2009). This implies that there is a higher possibility of housing bubbles with more speculative investors, who have more salaries. The investigation finds that housing starts affect house price positively, which indicates that the higher demand for houses increases the prices. This is in line with Li et al. (2018), which means the higher housing starts, the higher demand on houses so that increases the house prices in Beijing. This investigation also finds there is an inverse U-shape relationship between variable of housing-starts with floor-level and house prices. This suggests house price increases when the demand is lower than supply, and the excess supply of houses decreases the prices. This shows consistent finding with Maisel (1963) in terms of ‘a theory of fluctuation in residential construction starts’.

Figure 4.1 Outline of Findings in OLS and Panel Model



In Figure 4.1, the property characteristics have influenced the property price significantly, which indicates that consumer behaviour is an essential aspect of housing market (Rosen, 1979). Home size influences house price positively, which is in line with Fang et al. (2016) in terms of costs of China's characterised consumer behaviour of households. It implies that the larger home size in China increases the demand for housing. The higher floor level of houses, the higher prices. Whereas, in a tall building, the increasing prices from the lower floor level to the middle floor level; from the middle floor level to the upper floor level, the floor level influences house prices negatively. This result is similar to a previous study (Wong et al., 2005), which suggests the higher demand for middle floors. The number of bedrooms has a significant negative influence on property prices, which result is consistent with the find of Fahey (2016) in terms of privacy. The number of living rooms is not significant on property price in a fixed effects estimator of panel model. The houses facing north and south is significant and positive for the prices. This is because houses facing north and south have better natural ventilation and more daylight, which improves the natural quality of a house and its energy efficiency. This result is never found in previous studies (Bajari et al., 2010; Huang and Yin, 2015; Rosen, 1974; Zhang and Yi, 2017).

Figure 4.2 Outline of Findings in IV-GMM



In Figure 4.2, the investigation found several economic fundamentals and property characteristics are endogenous for property prices. In terms of economic fundamentals, mortgage down payment rates are endogenous. The central bank interest rates influence the mortgage payment rates positively because mortgage payment rates generally resemble the interest rates, which to be against the inflation. The inflation influences the mortgage payment rates negatively. The increase of the interest rate is tending to be against the irrational rise of inflation, which is consistent with findings of Irving (1911) in terms of 'quantity theory of money'. After adding the instrumental variables of interest rates and inflation, the coefficients of mortgage payment rates and the income increases. This result is in line with Gan et al. (2012). These results implicate that the government could restrain the rapidly increasing house prices indirectly through adjusting the central bank interest rates. The total investments in fixed assets and the local government budgetary expenditure influence mortgage payment rates positively, which is in line with the theory of 'conventional wisdom' (Galbraith, 1958). This is in line with Feltenstein and Farhadian (1987). However, money supply and the local government budgetary revenue influence mortgage payment rates positively, which is contrary to the 'conventional wisdom' (Galbraith, 1958) and the 'quantity theory of money' (Irving, 1911). It is not similar to Taylor (2000). This is because of China's rapid economic growth. As the good condition of economic growth, the increasing government revenue cannot restrain the demand for investments in housing market. The increase of government revenue means upward pressure on mortgage payment rates. Though the money supply increases, the aggregate demand for GDP is increasing rapidly so that this exceeds the amount of money supply, caused the increase of interest rate. After adding these instrumental variables, the investigation found that the coefficients of mortgage payment rates are increased respectively. These results implicate that the policy of fiscal deficit from Chinese government is efficient to indirectly restrain the rapid growth of house prices.

The investment in fixed assets and the local government general budgetary revenue affects housing demand negatively and significantly, which is in line with the finding of Naylor (1967) and Galbraith (1958) in terms of the theory of 'conventional wisdom'. After adding the instrumental variables, the investigation found that the coefficient of housing demand is decreased. This result implicates that the house price could be decreased through restrain investments and increase government revenue indirectly because investments and government revenue decreased the demand for houses.

Regarding Figure 4.2, house orientation influences the condition of the bedroom and the condition of living room significantly, which is in line with findings of Rosen (1974) in terms of the effects of house characteristics on the prices. The orientation factors of SE NW WE and SW negatively influence the number of bedrooms, respectively. The orientation factors of W negatively influence the number of the living rooms significantly. The orientation factors of WE affect the number of living rooms positively. This result is never been found in previous studies (Bajari et al., 2010; Huang and Yin, 2015; Zhang and Yi, 2017). After adding the instrumental variables in different models, the investigation found that the coefficients of BR are decreased. The coefficient of LR is increased. However, when the investigation considers the factor of floor level with number of bedrooms, the factor of Bedroom*Floor influences house prices positively and significantly with instruments of SE SW and SW NW respectively. The coefficient of Living_room*Floor increases. This means the more bedrooms that are facing southeast and southwest or that are facing southwest and northwest with higher floor level, the higher house price. The more living rooms that are facing west or east with higher floor level, the higher house price. This is because the house facing south and west have more extended daylight, which increases the temperature of the room, so that increase the electrical efficiency. However, the bedrooms facing southwest, southeast or northwest not only keeps daylight but also reduces west sunburn and improves natural ventilation to improve sleeping context. The living room improves west sunburn increasing the whole house temperature so that increase house efficiency. Moreover, the higher floor level of houses, the more efficient daylight and natural ventilation. Thus, this investigation finds the more numbers of rooms with proper orientation, the better condition of the room is which has good daylight and better natural ventilation. These results implicate that the government illustrate the policies about relating house structure is efficient.

This chapter overcomes the omitted variables of house characteristics, such as directions of house facing (orientation), house floor level (FR) and square of floor level (FR^2), which are never found in previous studies, leading to biased estimates of the implicit house price, compared with the previous studies (Rosen, 1974; Bajari et al., 2010). This research found there is an inverse U-shape relationship between floor level and house prices. Moreover, this investigation illustrated house orientation influences the condition of the bedroom and the condition of living room significantly and indirectly affects the house price in IV-GMM analyses, which improved the theoretical standpoint to understand the relationship between house characteristics and house prices.

In addition to the above, previous economic research has considered the variable of house demand that was designed primarily to determine the house prices. Based on the economic theory of supply and demand, excessive demand encourages the investor to have more confidence in investing in the property so that this increases the house prices (Rosenthal et al., 1991). Previous studies have found that the income elasticity of demand for housing is well below one (Rosen, 1974; Hoyt and Rosenthal, 1990; Rosenthal et al., 1991; Glaeser et al., 2008; Carrillo et al., 2014). In contrast, the present investigation applies Floor Space under Construction data of property land, which is housing starts multiple by floor level (HPP*FR), interpretation of property demand. This is because to housing starts is a potential standard which decides the final housing demand (Maisel, 1963) in terms of 'a theory of fluctuation in residential construction starts'. Moreover, this investigation employed the IV-GMM model to test the endogeneity of housing demand to the property prices respected to the instrumental variables with investment in fixed assets and local governments general budgetary revenue. This approach provides the determination of demand for houses be flexible with the economic conditions.

This investigation extends previous research in terms of the data sample, which provides an extended period (2002-2014) and a sample with the advantage of 17,143 transacted property records with detailed information, which linked transacted property records with property addresses to track the regional effects.

The application of panel analysis (i.e. fixed effects and random effects) extends the current literature by taking into account endogeneity in the IV-GMM framework with instrumental variables. In this regard, this investigation conceptually resembles Bajari et al., (2012), who investigate property prices the role of air pollution with hedonic regression. Empirical testing of the aforementioned issues provides a valuable tool for regulators in the Beijing area, because, to the best of our knowledge, it is the first study of its kind that examines all the above; it can also be useful for regulators in other industries, such as banking and insurance. In this chapter, the assessment and remediation of house price will depend on the understanding of their influencing factors.

4.1.4 Structure of This Chapter

The remainder of this chapter is organised as follows: Section 4.2 denotes the theory framework; Section 4.3 formulates the hypotheses that are tested in this chapter; Section 4.4 outlines the methodology and data; Section 4.5 analyses the estimation results; and Section 4.6 presents the concluding remarks.

4.2 Theoretical Framework

With the market-orientated economy in China in the recent past, houses are defined as commodities. Rosen (1974), who factor consumer behaviour into a hedonic regression, establishes the relationship between the product's price and its attributes. In practice, the regression coefficients are generally regarded as implicit or "hedonic" prices (Bajari et al., 2010). The implicit price can be described as the additional value of a product when individual attributes are increased while all other attributes remain fixed. For instance, in China's land market, the land with water facility is more expensive than that of without water facility, when the other attributes remain the same, such as size and other facilities. This is because the land with water facility has a particular attribute, which is the additional value of this land. Rosen (1974) established the hedonic regression to provide the house price based on utility-maximising behaviour. The estimate of implicit prices proposes that the consumer's willingness to pay for a small alteration in a particular attribute is marginal. Moreover, "these implicit prices can be used to recover marginal willingness to pay functions for use in valuing larger changes in attributes" (Bajari et al., 2010). However, it is uncertain whether there are omitted variables leading to biased estimates of the implicit prices. When applied to real data, several omitted house characteristics variables seem to be significant in the theoretical models. Moreover, Jim and Chen (2009) suggested that daylight and views from houses are significant factors affecting house prices. However, the previous studies ignore the condition of the room, which are the endogenous variables of house prices. This investigation tests these endogenous variables through the numbers of rooms with orientations, in order to explain the condition of the room which has good daylight and better natural ventilation.

The economic fundamentals have an essential relationship with the house prices. However, the endogenous economic fundamentals are leading to incorrect biased estimates of coefficients and result in an inefficient model. Mortgage payment rates could be regarded as an endogenous variable for house prices. The interest rates or mortgage payment rates are applied to adjust the inflation based on the 'quantity theory of money' (Irving, 1911). Moreover, interest rates will be influenced by fiscal policy referred to the theory of 'conventional wisdom' (Galbraith, 1958). The empirical endogenous tests of mortgage payment are scarce in the previous studies. The prior studies provide that income and unemployment rates are significant factors for the house prices. The property is an investment that allows the investors to achieve potential profit from the real estate market, with speculative and alternative incomes. This situation provides maximum stimulation to encourage investors to make a decision on their own deal. An individual property transaction is dominated by what the investor believes will happen to the market in the future without regard to any possible distortions (Cheng et al., 2014). Based on the theory of 'distortions beliefs' (Cheng et al., 2014), the investors ignored the risk of low demand, referred to income and unemployment rates, may have fostered the financial circumstances that enabled property prices to rise alongside credit expansion, and subsequently spark the crisis (Gennaioli et al., 2013). However, the previous studies neglect the endogenous of income. Based on the time value of money, the money supply influences the nominal value of the money referred to the inflation. If a person's wage is fixed or the rate of increase is small for a long-term, the inflation would have a significant effect on the living standards. According to 'a theory of fluctuation in residential construction starts' (Maisel, 1963), housing starts is a potential standard which decides the final housing demand. However, referred to Naylor (1967), fiscal policy influences the housing starts indirectly based on 'conventional wisdom' (Galbraith, 1958). However, the previous studies neglect the endogenous of housing starts.

4.3 Literature Review and Hypotheses

In China, the accurate measurement of house prices is essential to monitor economic fundamentals (Hui and Gu, 2009; Li and Chand, 2013; Li et al., 2018; Shen and Liu, 2004; Yu, 2010) and investment behaviour (Huang and Yin, 2015; Wong et al., 2005; Zhang and Yi, 2017). Zhang and Yi (2017) provide that the rising house prices may cause a symptom of a housing bubble. Gennaioli et al. (2013) illustrated the investors ignored the risk of low demand, referred to income and unemployment rates, may have fostered the financial circumstances that enabled property prices to rise alongside credit expansion, and subsequently spark the crisis. Chen et al. (2012) applied economic fundamentals such as interest rates, inflation, and cost of supply to investigate whether a bubble existed in the Beijing housing market from 1998 to 2010. They revealed that the Beijing house price index was more significant than the equilibrium value, based on the relative economic fundamental variables from 2004 to 2007. Therefore, it is valueable to provide an empirical analysis of the effect of housing fundamentals on property price in beijing.

The previous study employs a house price index of Beijing on hedonic models (Zhang and Yi, 2017), which explore the relationship between house attributes and house price. They find that most housing attributes are valued differently across the distribution of house prices, and the distribution of house prices changes based on the different value of housing attributes. Huang and Yin (2015) find the house price was affected by house characteristics significantly between 2000 and 2007 in Wuhan, China. Moreover, Zhang and Yi (2018) employ a comprehensive housing transaction dataset and analyse the house price between 2012 and 2015 in China. These studies confirm house characteristics causes the changes of the house price.

4.3.1 Economic Fundamentals Determinants

Referred to Wen and Goodman (2013), house price is determined by economic fundamentals in a city level. The previous empirical studies applied with supply and demand, and they use macroeconomic variables, such as income, mortgage payment rates, and house starts to explain the house prices. Because these economic fundamentals are relative to the supply and demand of the local housing market, which has impacts on house prices.

According to Milne (1991), there is a positive correlation between income level and house prices. Capozza et al. (2004) suggest that real incomes are the essential factors that are determinants of real house prices. Shiller (2007) suggests that interest rates, income levels and inflation influence house prices. Chen and Patel (1998) find that house prices and income exist in a state of equilibrium in Taipei. Through analysing the Spanish property price proportion, Fernández-Kranz and Hon (2006) suggest that income is the most influential factor in house prices. Riddel (2011) argues that contagious price and income growth resulting from native expectations have effects on the Las Vegas housing market. In China, Ge and Wu (2017) demonstrate the relationship between per capita income and the house prices in China. They find the steady growth in per capita income may drive property prices up; however, the house transaction price has been growing much faster than the average income from 1997 to 2017. The price-to-income ratio sharply increased from 6.6 in 2003 to 7.9 in 2005, and there is a decline from 7.2 in 2008 to 8.5 in 2009. The results indicate that the rapidly increasing house prices in China are due to the unequal distribution of individual wealth. Hui and Gu (2009) conclude that income is a significant factor affecting house price levels, causing a bubble of real estate activity in October 2007 at around 43% of the housing market price in Guangzhou city. Shen and Liu (2004) provide per capita disposable income significantly influence about 60% of the house price in China with panel data on 14 cities in China from 1995 to 2002. Thus, this investigation has a hypothesis that states:
H1. The income does not affect the property prices.

Kohn and Bryant (2010) finds that mortgage payment rates had a significant impact on the real estate market within the long-term analysis from 1990 to 2007 in the US economy. Lee (1997) studied a test bubble and suggested that irrational mortgage down payment and money supply drove up house prices in Korea between 1964 and 1994. Mints (2007) suggested that mortgage payment rates are an essential influence on the housing bubble in the Russian housing market. The determinant of defaulting on loans and the prepayments for housing loans could cause the volatility of house prices (Miles, 2008). For China, the down payments in mortgage sample had been consistently above 30% across Tier 1-3 cities in China (Fang et al., 2016). They also find that the average down payment ratio of mortgage loans made to the group with income in the lowest 10% of all mortgage borrowers was even slightly higher

than that of the group with income in the middle quintile of all mortgage borrowers. Qi and Cao (2007) investigate the relationship between property prices and bank lending in China over the period 1999Q1–2006Q2. They find short- and long-term causality from bank lending to property prices. Peng et al. (2005) model 31 Chinese provinces and major cities from 1998 to 2004 and find that credit expansion by the four large state-owned banks does not feed property-price inflation. Yu (2010) applies panel data econometrics to achieve the conclusion that the mortgage payment rate has a negative effect on house prices from 1998 to 2007. Li and Chand (2013) employ annual data with 29 provinces of China from 1998 to 2009 and provide that the mortgage payment rate influence China's urban house prices by about 0.5% negatively. Thus, this research has a hypothesis that states:
H2. Mortgage payment rates do not influence property prices.

According to Kohn and Bryant (2010), excessive demand for housing causes house price volatility in the US economy. Case and Shiller (2003) maintain that buyer expectations lead to higher prices and are a predictor of the future of a housing market, which emphasises the correlation between house demand and house prices. Mayer and Quigley (2003) agree with many of the conclusions of Case and Shiller (2003). Smith and Smith (2006) conclude that the dramatic increase in house prices as well as in the expectations of buyers in 2005 was in response to the promising investment opportunities found in home ownership and not the existence of a house price bubble. Referred to Maisel (1963), housing starts are a potential standard which decides the final housing demand in terms of 'a theory of fluctuation in residential construction starts'. In this research, the investigation uses floor space of property under construction, which is the size of started buildings, instead of the demand quantity of properties. For China, Ge and Wu (2017) examine the relationship between the net supply and the real transaction price from 1991 to 2011 in China. They detect the excess supplies coexisted with steady increases in real transaction prices. It implies that the price mechanism failed to clear out supply and demand in the market. Li et al. (2018) provide that the ratios of residential floor space under construction to floor space sold have been increasing since 2004 in Beijing and Beijing's commodity housing average sale price increased by 15.5 per cent each year after 2004. Thus, this chapter has a hypothesis that states:
H3. The property demand has no effects on property prices.

4.3.2 House Characteristics Determinants

Rosen (1974) suggests that structural characteristics of the house, such as size, number of rooms, the location within the market and the time value of properties influence the property prices. Malpezzi (2002) and Bajari et al. (2012) also illustrate that the hedonic model is appropriate for estimating the coefficients of valuing implicit prices. This investigation also considers the omitted variables of implicit prices with orientation and floor level of the property. Wong et al., (2005) suggest that the highest demands are for properties located on the middle floors of tall buildings. Jim and Chen (2009) suggest that daylight and views from houses are significant factors affecting house prices. Regarding the previous studies in China, Wilson and Parisi (2006) provide that south-facing apartment increases housework efficiency such as drying the clothes. Yao (2014) detects that the south-facing house saved facilitates energy by keeping the indoor area warm during winter. Zhang and Yi (2017) employ a comprehensive micro-level dataset of newly-built residential housing units in Beijing from 2013 to 2015 with OLS estimation quantile regression and found the number of bedroom and number of living room increase house price by 9.77% and 14.47% respectively. They also provide there is a positive relationship between house price, size of living area and floor level. Accordingly, this chapter examines the determinants of changes in Beijing property prices in the context of property characteristics factors and the following hypothesis:

H4. Property size does not influence the property prices.

H5. Number of bedrooms does not influence the property prices.

H6. Number of living rooms does not influence the property prices.

H7. The floor level of the property does not influence the property prices.

H8. The orientation of the property does not influence the property prices.

Meen (1996) finds that house-price movements are unidirectional, spreading from urban centres to the periphery. Larraz-Iribas and Alfaro-Navarro (2008) provide evidence of co-integration among regional prices, with physical proximity increases the likelihood of price co-integration. Oikarinen (2006) illustrates that the increase in Finland’s house prices began in Helsinki, the political and economic centre of the country, and then expanded to outlying areas. For China, Huang and Yin (2015) provide that house characteristics, environmental sustainability elements had the impacts on house prices. The home buyers are willing to pay more for housing clusters with proximity to the city centre (Huang and Yin, 2015). Thus, this investigation uses the cross-sectional study with regional clusters to analyse the changes in the house prices.

4.3.3 Endogenous Variables and Instruments

4.3.3.1 Mortgage Payment Rates and Inflation

Regarding the 'quantity theory of money' (Irving, 1911), the inflation is decided by money supply and money demand. When the money supply increases, the price of goods turns upwards, referred to the decreasing value of the currency. According to Irving (1911), the central banks are generally under a fractional-reserve banking system which increases the interest rate in order to be against the irrational rise of inflation. In other words, the correlation between interest rates and inflation are inverse. Diversely, the inflation has a relationship to the mortgage payments. If a person borrowed a fixed amount of money, the increasing inflation helps this person pay back a lesser amount of money. The mortgage payments are the costs of borrowing to funds. The mortgage payment rates generally resemble the interest rates against the inflation under the banking system. For China, Gan et al. (2012) employ a proprietary dataset from branches of the Construction Bank of China from 2004 to 2009 and provide the mortgage payment rate is influenced by interest rate by 1.2% positively and significantly. Thus, this investigation has hypotheses that:

H9. The central bank interest rates (IR) do not influence the mortgage payment rates (MR).

H10. The inflation (CPI) does not influence the mortgage payment rates (MR).

4.3.3.2 Income and Inflation

The central bank interest rates and inflation are significant factors to the income of persons. Referred to Irving (1911), the money supply influences the nominal value of the money referred to the inflation. If a person's wage is fixed or the rate of increase is small for a long-term, the inflation would have a significant effect on the living standards. Meanwhile, the inflation is relative to the interest rates. For China, Deng et al. (2018) detect that the overheating in real estate markets are influenced by the movements in bank credit. The income of the household, representing a fundamental of house prices, provides a bound on the latter in an economy without financial markets. However, the mortgage loans employed to finance housing purchases, which may disconnect house prices from the household-income fundamental. Horioka and Wan (2007) conduct a dynamic panel analysis of the determinants of the household saving rate in China between 1995 and 2004. They find the real interest rate has a significant positive impact on the household saving rate, which is the difference between income and expenses, suggests that the interest elasticity of saving is positive and is consistent with the permanent income. Thus, this investigation has hypotheses that:

H11. The central bank interest rates (IR) do not influence the income (IC).
H12. The inflation (CPI) does not influence the income (IC).

4.3.3.3 Fiscal Policy and Mortgage Down Payment

Referring to the theory of 'conventional wisdom' (Galbraith, 1958), the increased spending of government increases the aggregate demand for GDP; subsequently, the rise of aggregate demand for GDP will increase the price of goods. The interest rates will be increased, when the price increases, to be against the irrational rise of inflation Irving (1911). The interest rates have a positive relationship with mortgage payment rates. Thus, this investigation hypothesis that the fiscal policy does not influence the mortgage payment rates. Regarding Irving (1911), money supply and money demand influence the interest rate. The money supply affects mortgage payment rates referred to interest rates. Feltenstein and Farhadian (1987) illustrate that changes in the money supply are explained by the government deficit, the wage bill of the government and state enterprises in China. Taylor (2000) provide the instruments of fiscal policy change aggregate demand and influence the monetary policy indirectly. Land sales revenues are regarded as significant collaterals for local governments to increase debt financing in China (Liu and Xiong, 2018). Regarding the fiscal measures and monetary policy instruments influence the Chinese housing market indirectly through the loan of the bank system, this investigation has hypotheses that:
H13. Total investment in fixed assets in the whole country (IFA) does not influence the mortgage payment rates (MR).
H14. Money supply (MS) does not influence the mortgage payment rates (MR).
H15. Local government general budgetary revenue (GR) does not influence the mortgage payment rates (MR).
H16. Local government general budgetary expenditure (GE) does not influence the mortgage payment rates (MR).

4.3.3.4 Fiscal Policy and Housing Starts

According to Naylor (1967), the fiscal policy influences the housing starts indirectly. Local revenue policies regulate the tax rate of income, company's profit, business or contributions to social insurance, to adjust the economic conditions. Based on the theory of 'conventional wisdom' (Galbraith, 1958), the increasing tax rates reduces the aggregate demand for GDP;

subsequently, the changes in aggregate demand for GDP will indirectly influence housing starts by the diversities of intermediate economic factors, such as income, employment and prices (Naylor, 1967). Referred to 'a theory of fluctuation in residential construction starts' (Maisel, 1963), housing starts is a potential standard which decides the final housing demand. On the other hand, Naylor (1967) suggests that an increase of investment in fixed assets will lead to a rise in GDP, referred to conventional wisdom. The changes of GDP influence the housing starts, which is regarded as the housing demand. For China, Koss and Shi (2018) mentioned that the central government policies, such as "freeze" in transactions, the purchase restrictions and increased land supplies, cannot be regarded as these measures have changed the fundamentals of the residential housing market, particularly with regards to damping the speculative fervour. This is because these policies curbed the house prices in short-term but did not correct the fundamental mismatch in the market between supply and demand or cool the enthusiasm of property speculators in the over-heated cities. In this research, the investigation uses floor space of property under construction (HPP), which is the size of started buildings, instead of the demand quantity of properties. Thus, this chapter has a hypothesis that states:

H17. Total investment in fixed assets in the whole country (IFA) does not influence house demand (HPP FRHPP FR2HPP).

H18. Local government general budgetary revenue (GR) does not influence house demand (HPP FRHPP FR2HPP).

4.3.3.5 Property Characteristics

Rosen (1974) suggested that structural characteristics of the house, such as size, number of rooms, the location within the market and the time value of properties influence the property prices. Malpezzi (2002) and Bajari et al. (2012) also found that the hedonic model is appropriate for estimating the coefficients of valuing implicit prices. This investigation also considers the omitted variables of implicit prices with orientation and floor level of the property. Jim and Chen (2009) suggested that daylight and views from houses are significant factors affecting house prices in Hong Kong. Thus, the more numbers of rooms with an appropriate orientation, the better condition of the room are which has good daylight and better natural ventilation. Accordingly, this chapter examines the following hypothesis:

H19. House orientation (Orien) does not influence the condition of the bedroom (BR BRFR)

H20. House orientation (Orien) does not influence the condition of the living room (BR BRFR)

4.3.4 Methodology Review

With regard to other methods of analysing house prices, Case and Shiller (1989, 1990) find that forecast errors in house prices follow an autoregressive process. Bourassa et al. (2009) and Hui and Yue (2006) study the influences on house prices using different compositions of fundamental supply-side and demand-side price factors. Mankiw et al. (1985) suggest that modified volatility tests are sufficient for the real estate market. Diba and Grossman (1998) illustrate unit-root tests, and Black et al. (2006) illustrated VAR models on the valuation of house prices. Himmelberg et al. (2005) improve house pricing models with growth rates in property prices, price-to-rent ratios, and price-to-income ratios. Campbell and Shiller (1987) tested the presence of a bubble in the equity market with the co-integration methodology, which was developed by Granger and Engle (1987). While the hedonic pricing model is appropriate for the capture of the Chinese housing market price. In terms of the rapid extension of Chinese cities, new apartments or houses have been built dispersed from the city centre. The developed urban area at the national level expanded from 19,844 square kilometres in 2003 to 34,867 square kilometres in 2013 (Fang et al., 2016). This significant increase of urban residential land parcels implies that unobserved time-varying characteristics in terms of urban area growth dispersed from the city centre result in biased house price. Regarding this situation, it is suggested to employ the hedonic pricing model to capture the Chinese housing market price.

4.4 Methodology and Data

4.4.1 Methodology

This investigation explores the underlying relationship between property characteristics and the economic forces that determine them, and their impact on property prices. It will draw upon previous studies which have revealed relevant information in this area (Case and Shiller, 1989, 1990; Himmelberg et al., 2005; Hui and Yue, 2006; Mankiw et al., 1985). The property price equation is employed to determine whether property characteristics and economic performance are influencing property prices (Equation 4.1). Coefficients for variables are estimated using the ordinary least-square (OLS) regression.

$$P_{it} = \alpha_0 + a_1 E_{it} + a_2 C_{it} + \sum_{i=1}^{n} \lambda_i Z_i + \varepsilon_{it} \tag{4.1}$$

where i denotes an individual property; t represents the date of property transacted; i refers to the region where P_{it} is a house price measure; and E_{it} represents the economic fundamental variables that is hypothesised to influence property prices. C_{it} represents the property characteristics variables. Z_i is used as a vector representing the control variables, λ_i is an estimated coefficient for control variables, and ε_{it} is the random error.

Panel data analysis is conducted by taking account of group effects and time effects. Initially, fixed effects and random effects are examined. The decision to select the appropriate model is based on the implementation of the Hausman Test. To examine property price determinants, the investigation uses the general panel data regression model, in the following equations:

$$P_{it} = \alpha_0 + a_1 AS_{it} + a_2 FR_{it} + a_3 FR_{it}^2 + a_4 BR_{it} + a_5 LR_{it} + +a_6 logHPP_{it} + a_7 FR_{it} * logHPP_{it} + a_8 FR_{it}^2 * logHPP_{it} + a_9 HPI_{it} + a_{10} MR_{it} + +a_{10} logIC_{it} + d_1 Orien + d_2 Region + d_3 Year \tag{4.2}$$

and fixed effects:

$$\varepsilon_{it} = \mu_i + v_{it} \tag{4.2.1}$$

and random effect:

$$\mu_i \sim i.i.d. N(0, \sigma_\mu^2) \tag{4.2.2}$$

$$v_{it} \sim i.i.d. N(0, \sigma_v^2) \tag{4.2.3}$$

where it is the subscript indicating property i at time t. P is used as dependent variables to represent the 10^{-3} times of property price. Regarding independent variables that this investigation uses to test for property characteristics, these include property size in square metres (AS), floor level of the property (FR), number of bedrooms in the property (BR), number of living rooms in the property (LR), dummy variable for the window orientation of the property (O), dummy variable for the region in which the property belongs, and the year in which the property was transacted. The mortgage payment rates (MR), house price index (HPI) and income (IC), are treated as the economic factors that influence property prices. In fixed effect, μ_i are regions of property defined and time-invariant effects. In addition, random effect assumes that two error components are independent from each other.

It is worth mentioning that, this investigation estimates the factors with the square of floor level (FR_{it}^2) and interactions between floor level and house planned permissions ($FR_{it} *$

$logHPP_{it}$). Based on Wong et al. (2005), the greatest demand for houses is located on the middle floor levels of tall buildings. In the past, middle floor level houses were popular because the price was not as high when compared to the top floor level houses. Meanwhile, daylight and views of houses located on middle floor levels is similar to house on top floor levels (Jim and Chen, 2009). Thus, the demand for houses located on middle floor levels increased, causing prices for those properties to rise. In the recent period, houses located on middle floor levels have the highest price in a tall building. Thus, this research estimates FR_{it}^2 to represent the influence of floor level to house prices and estimated $FR_{it} * logHPP_{it}$ to represent the interactions between floor levels and house demands.

Given the nature of this research, least squares estimation methods generate biased and inconsistent estimates (Baltagi, 2001). Additionally, a number of explanatory variables are endogenous. To address these concerns, this investigation uses the generalised method of moments (GMM) method, which accounts for endogeneity by using alternative independent variables that are suspected to suffer from endogeneity. To examine property price determinants, this investigation employs the following equations:

$$P_{it} = \alpha_0 + \gamma X_{it}' + \sum_{i=1}^{n} \lambda_i Z_i + \varepsilon_{it} \tag{4.3}$$

$$X_{it}' = [y_{2i}' \; x_{1i}'] \tag{4.3.1}$$

$$z_i' = [x_{1i}' \; x_{2i}'] \tag{4.3.2}$$

where i denotes an individual property; t represents the date of property transacted; P_{it} is property prices. X_{it}' combines endogenous variables and exogenous variables and the dependent variable is denoted by y rather than y_1. This investigation similarly combines the instruments for these variables (Equation 4.3) which is hypothesised to influence property prices with indirect effects. Z_i is used as a vector representing the control variables, λ_i is an estimated coefficient for control variables, and ε_{it} is the random error.

It is important that this chapter estimates the interactions between the number of bedrooms and floor level ($BR * FR$); and the interactions between the number of living rooms and floor level ($LR * FR$) in the models respectively. This is because the investigation wants to control the floor level effects when the investigation analyses the influences of orientation effects for house prices.

Baltagi (2001) argued that employing the values of the other variable regressors as instruments can increase consistency and efficiency of the model. The IV-GMM model employed the instrumental variables to improve the efficiency of the model. Meanwhile, the IV-GMM method restricts unobserved heterogeneity and limited the consistency of the dependent variable [29]. To deal with this, the independent variables employed in this investigation refer to the existing literature. Subsequently, the hypotheses are examined by the endogenous test. In the hypotheses, the coefficients of the independent variables are not significant and are individually equal to zero. If the null hypothesis is not rejected, the model is not efficient so that to modify the equation. With regards to the efficient model, the null hypothesis should be rejected so that the independent variables are significant in the general regression. Alternatively, the investigation could reduce the number of non-significant variables to estimate a confining hypothesis. Such estimations yield consistent estimations of the parameters. The coefficients of independent variables are respectable, and refer to the restriction for the number of independent variables.

4.4.2 Data

Beijing is located in the northwest region of China, between longitude 115°25’-117°30’E and latitude 39°28’-41°05’N and covers an estimated area of 1.6 × 104 km^2. In its examination of real estate development and the limited data that is available, this investigation addresses the area of Beijing which the government has demarcated as the city’s core area. In the empirical analysis for this study, a sample of 17,143 transacted property records have been examined, fulfilling the requirements for this investigation. The sample period spans 2002 to 2014. The data have been retrieved from the largest available real estate information websites: Soufang DataStream and the Beijing municipal commission on house and urban-rural development website. The numbers of property transaction records shown are as follows:

Table 4.1 Number of Property Transaction Records

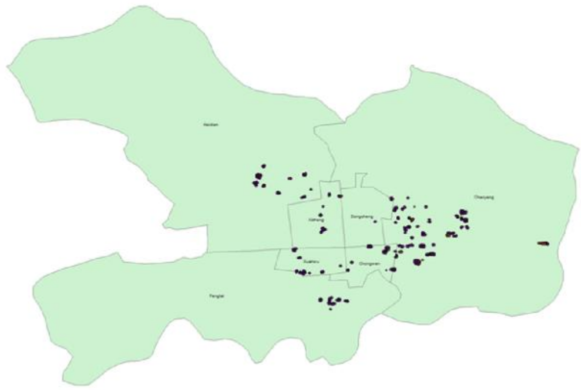
Year	200	200	200	200	200	200	200	200	201	201	201	201	201
Sample	434	642	734	814	880	937	951	105	101	101	105	370	391

This chapter investigates the determinants of property price in seven districts of Beijing. The transacted property records include the longitude and latitude, in order to track the records respectively in alternative areas.

[29] See Baltagi (2001) for econometric analysis of panel data.

Figure 4.3 Beijing Map and Study Area

Map of Beijing



Study Area

Figure 4.3 illustrates the map of Beijing with the whole city view and the study area which includes seven Beijing urban core districts: Dongcheng district, Xicheng district, Xuanwu district, Chongwen district, Haidian district, Chaoyang district and Fengtai district. Several significant residential areas have been included in this study area. The points on the map in Figure 4.3 are the locations of property transactions which have the coordinate records.

Table 4.2 provides the descriptive statistics for 17,143 house transactions in Beijing. Mean of the variables, standard deviation of the variables, minimum of the variables and maximum of the variables are employed in this table. House price is the dependent variable, and the other samples are independent variables. In order to refrain from the influence of collinearity issue, the investigation established collinearity diagnostics. Table 4.3 summarises the coefficients of pairwise correlations including the endogenous variables and exogenous variables in this investigation.

Table 4.2 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
House Price	17,143	36.87	24.74	0.27	937.5
Size	17,143	122.9	64.13	16.36	656
Floor Level	17,143	19.51	9.24	1	66
Number of Bedrooms	17,143	2.22	0.96	1	8
Numbers of Living rooms	17,143	1.47	0.64	0	4
House Planning Permissions	17,143	4.07	0.07	3.88	4.14
House Completed Permissions	17,143	3.44	0.05	3.35	3.58
House Price Index	17,143	109.8	7.08	97.4	122
Mortgage Payment Rates	17,143	0.07	0.00	0.058	0.078
Unemployment Rates	17,143	0.01	0.00	0.012	0.021
Income	17,143	4.73	0.16	4.32	4.89
Central Bank Interest Rates	17,143	0.06	0.005	0.053	0.075
Consumer Price Index	17,143	102.2	1.76	98.2	105.6
Gross Regional Product	17,143	4.14	0.21	3.63	4.33
Total Investment in Fixed Assets in the Whole Country	17,143	3.70	0.17	3.25	3.84
Local Governments General Budgetary Revenue	17,143	3.37	0.27	2.73	3.60
Local Governments General Budgetary Expenditure	17,143	3.42	0.26	2.80	3.66
Gross Output Value of Construction	17,143	3.67	0.27	3.02	3.91
Money Supply	17,143	5.82	0.26	5.20	6.08
South	17,143	0.14	0.35	0	1
North	17,143	0.07	0.26	0	1
East	17,143	0.10	0.29	0	1
West	17,143	0.07	0.26	0	1
Southeast	17,143	0.11	0.31	0	1
Southwest	17,143	0.08	0.27	0	1
Northeast	17,143	0.05	0.21	0	1
North and South	17,143	0.32	0.47	0	1
West and East	17,143	0.03	0.17	0	1
Region ID	17,143	4.78	1.40	1	7
Year	17,143	2010	3.7	2002	2014

Table 4.3 Coefficients of Correlation

	Price	Size	Floor_level	Bedroom_nums	Livingroom_nums	House_planning_permissions	House_price_index	Mortgage_payment_rate	Income
Price	1								
Size	0.0452	1							
Floor_level	0.0451	-0.0016	1						
Bedroom_nums	-0.0054	0.7939	-0.1626	1					
Livingroom_nums	0.0148	0.6031	-0.0412	0.6361	1				
House_planning_permissions	0.5959	-0.094	0.0557	-0.0844	-0.0581	1			
House_price_index	0.2446	-0.035	0.0322	-0.0366	-0.0325	0.312	1		
Mortgage_payment_rate	0.1495	-0.0075	0.0115	-0.0131	-0.008	0.2786	0.149	1	
Income	0.6255	-0.0918	0.0554	-0.0895	-0.0571	0.9123	0.3044	0.3131	1
Mean VIF	2.93								

4.5 Empirical Findings

4.5.1 OLS and Panel Results

The results of the examination of the determinants in the property sector are presented in the OLS and panel data-property regression models and are analysed by using different estimators.

This model has estimated OLS regression, cross-sectional regression with fixed effects and cross-sectional regression with random effects in Table 4.4. The robust regressions are represented in columns with "_r". The fixed effects estimation and the random effects estimation is employed in the data with time series in the panel structure. Year effects are attributed to apprehend the changes in house price appropriately across time. The Breusch-Pagan test shows the value with 9.66 and 0 of the p-value, which strongly rejects the null hypothesis. This means there is heteroscedasticity in the OLS estimator indicating the regression is not efficient. The Breusch-Godfrey test shows the value with 130.6 and 0 of the p-value, which rejects the null hypothesis that there are conditionally uncorrelated observations. In order to select an appropriate model between fixed effects regression and random effects regression, the estimations of regressions show that the F-statistic for fixed effects is significant at 1% and Wald chi2 is significant at 1% for random effects, implying that the model is good and coefficients in the model are different from zero. The p-value of the Hausman test is zero; this means that the fixed effects regression is more appropriate for this model. The Wooldridge test is applied to test the conditionally uncorrelated observations in the panel models. With the values of 0.67 and 0.45 of the p-value, the result accepted the null hypothesis that there are conditionally uncorrelated observations. The heteroscedasticity test (likelihood-ratio test) suggests the value of 3999 and p-value of 0, which strongly rejects the null hypothesis that there is conditional homoscedasticity. This suggests that there is conditional heteroscedasticity in the panel model. According to the Friedman test, the statistics are distributed by chi-square. The result of the Friedman test suggests that there is a cross-sectional correlation, which rejects the null hypothesis with 0 of the p-value.

Table 4.4 Regression Results Using OLS, Fixed Effect and Random Effect with Tests for House Prices

$$P_{it} = \alpha_0 + a_1 AS_{it} + a_2 FR_{it} + a_3 FR_{it}^2 + a_4 BR_{it} + a_5 LR_{it} + +a_6 logHPP_{it} + a_7 FR_{it} * logHPP_{it} + a_8 FR_{it}^2 * logHPP_{it} + a_9 HPI_{it} + a_{10} MR_{it} + +a_{10} logIC_{it} + d_1 Orien + d_2 Region + d_3 Year$$

	OLS	**OLS_r**	**Newey**	**Fixed**	**Fixed_r**	**Random**	**Random_r**
Size	0.0548*** (14.14)	0.0548*** (4.10)	0.0548*** (12.75)	0.0617*** (16.58)	0.0617*** (3.78)	0.0548*** (14.14)	0.0548*** (4.10)
Floor_level	21.70*** (8.52)	21.70 (1.61)	21.70*** (7.55)	22.41*** (9.29)	22.41 (1.84)	21.70*** (8.52)	21.70 (1.61)
Floor_level^2	-0.316*** (-5.63)	-0.316 (-1.63)	-0.316*** (-5.85)	-0.304*** (-5.72)	-0.304 (-1.87)	-0.316*** (-5.63)	-0.316 (-1.63)
Bedroom_nums	-2.101*** (-7.67)	-2.101*** (-5.31)	-2.101*** (-8.14)	-2.630*** (-10.08)	-2.630*** (-6.50)	-2.101*** (-7.67)	-2.101*** (-5.31)
Livingroom_nums	0.164 (0.55)	0.164 (0.50)	0.164 (0.54)	0.447 (1.60)	0.447 (0.89)	0.164 (0.55)	0.164 (0.50)
House_planning_permissions	118.2*** (14.54)	118.2** (2.60)	118.2*** (11.11)	118.0*** (15.31)	118.0** (2.98)	118.2*** (14.54)	118.2*** (2.60)
Floor*House_permissions	-5.495*** (-8.78)	-5.495 (-1.63)	-5.495*** (-7.67)	-5.594*** (-9.43)	-5.594 (-1.84)	-5.495*** (-8.78)	-5.495 (-1.63)
Floor^2*House_permissions	0.0815*** (5.90)	0.0815 (1.70)	0.0815*** (6.06)	0.0777*** (5.95)	0.0777 (1.92)	0.0815*** (5.90)	0.0815* (1.70)
House_price_index	0.201*** (9.46)	0.201*** (10.13)	0.201*** (7.18)	0.193*** (9.62)	0.193*** (11.27)	0.201*** (9.46)	0.201*** (10.13)
Mortgage_payment_rate	-292.0*** (-9.58)	-292.0** (-3.46)	-292.0*** (-12.59)	-278.7*** (-9.70)	-278.7** (-3.64)	-292.0*** (-9.58)	-292.0*** (-3.46)
Income	77.10*** (35.48)	77.10*** (11.62)	77.10*** (38.05)	79.38*** (38.70)	79.38*** (10.91)	77.10*** (35.48)	77.10*** (11.62)
North & South	2.318*** (6.25)	2.318 (1.84)	2.318*** (4.67)	2.478*** (7.01)	2.478 (1.78)	2.318*** (6.25)	2.318* (1.84)
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-809.2*** (-27.99)	-809.2*** (-3.99)	-809.2*** (-19.82)	-823.9*** (-29.97)	-823.9*** (-4.38)	-809.2*** (-27.99)	-809.2*** (-3.99)
N	17143	17143	17143	17143	17143	17143	17143
R-square	0.43	0.43		0.462	0.462	0.43	0.43
Breusch-Pagan test p-value	9.66 0						
Breusch-Godfrey LM test p-value	130.6 0						
Hausman test p-value				679.9 0			
Wooldridge test p-value				0.67 0.45			
Likelihood-ratio test p-value				3999 0			
Friedman's test p-value				264.5 0			

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation.

Based on the results of the fixed effects regression, the size of the property leads to an increase of 0.062% in property prices. Thus, the hypothesis H4 is rejected, which means property size influences the property price. This result is in line with Zhang and Yi (2017) who find there is a positive relationship between house price and size of living area in Beijing. It implies that the larger-size house increases the demand for housing in the Beijing housing market. Home size in China influences the housing demand in terms of China's characterised consumer behaviour of households (Fang et al., 2016). In respect of the floor level (FR) of the property, there is a significant positive relationship between property prices with 22.4% and negative relationship on property prices with FR^2. The hypothesis H7 is rejected. This means the floor level influences the house price positively from the lower floor level to the middle floor level in a tall building. However, from the middle floor level to the upper floor level, the floor level influences house prices negatively. This result is similar to a previous study (Wong et al., 2005). It implies that the household in Beijing preferred to buy a similar condition house with the lower price. The number of bedrooms has a significant negative influence on the property prices with 2.63%. The hypothesis H5 is rejected. This situation may be based on privacy. According to Fahey (2016), one-bedroom rents are more expensive than rents for two-bedrooms. The number of living rooms is not significant on property prices in a fixed effects estimator. The hypothesis H6 is accepted. This result is not in line with Zhang and Yi (2017). This may be because most of houses in Beijing contains only one bedroom, which is not a significant factor to the house price. Regarding the property orientation as a vector dummy variable, the north and south factor is significant and positive, which means that houses facing north and south have an increased price of 2.48%. The hypothesis H8 is rejected. This result is found in the previous studies (Jim and Chen, 2009). However, this increase is because houses facing north and south have better natural ventilation and more daylight, which improves the natural quality of the house as well as its energy efficiency. Thus, it is similar to Jim and Chen, (2009) who suggested that daylight and views from houses are significant factors affecting house price. In terms of the economic factors, the mortgage payment rates have a significant negative influence on property prices with 278.7%. Thus, hypothesis H2 is rejected. This result is similar to that of Fang et al. (2016), who find mortgages are necessary for many households in China, and Kohn and Bryant (2010), who find that the mortgage payment rates have a significant negative relationship to property price. This result also confirms that of Yu (2010) and Li and Chand (2013), who provided the mortgage payment rate influence China's urban house prices negatively by data between 1998 and 2009. The House Price Index (HPI) has a 0.19%

positive influence on property prices. The average income of citizens influences the property prices significantly and positively with 79.4%. Thus, the hypothesis H1 is rejected. This result is in line with Hui and Gu (2009) and Shen and Liu (2004), who provide income significantly influence the house price in China. The demand quantity of properties (Floor*House_permissions) has an inverse U-shape relationship with house prices. Thus, the hypothesis H3 is rejected. This result is not similar to Li et al. (2018), who provide the ratios of residential floor space under construction to floor space increase house price by 15.5 per cent each year after 2004. This is because the thesis improved the method of calculating house demand, which is more flexible with an inverse U-shape relationship to explore the house price and house demand. It implies that price mechanism failed to clear out supply and demand in Beijing housing market (Ge and Wu, 2017). The factors are related to economic performance in terms of property price and are statistically significant, as well as consistent with previous studies (Antolin and Bover, 1997; Lee, 1997; Chen and Patel, 1998; Shiller, 2007; Mints, 2007; Miles, 2008). Although some studies were undertaken in different countries, all of the results corresponded with economic theory. Based on such findings, economic factors have a significant influence on property prices in Beijing.

4.5.2 Generalised Method of Moments (GMM)

Regarding the test of error terms unrelated to regressors, the null hypothesis is rejected, meaning that the regressors have endogeneity. With respect to linear instrumental variables regression, this investigation applies and tests the instrumental variables and endogeneity in order to establish IV-GMM models.

In order to identify the relationship between mortgage payment rates (MR) and house prices, this research employs mortgage payment rates as an agent variable, and employs central bank interest rates and CPI as the instrumental variables by an endogenous variable of MR. Based on the empirical results of first stage regression referred to IV-GMM, the central bank interest rates (IR) influence the mortgage payment rates (MR) positively and significantly, which p-value of IR is 0 (Table A.9). According to the results, when the interest rates have an increase of 1%, the mortgage payment rates will be increased by 0.95%. The hypothesis H9 is rejected. This result is similar to Irving (1911), who provide the mortgage payment rates generally resemble the interest rates against the inflation under the banking system. It implies that the mortgage payment rate is influenced by interest rate positively and significantly, in line with Gan et al. (2012). The inflation (CPI) influences the mortgage payment rates (MR) negatively and significantly, which p-value of CPI is below 0.05 (Table A.9). Thus, the hypothesis H10 is rejected. This result provides that if inflation decreases by 100%, the mortgage payment rates will increase by 0.004%. These results confirm the 'quantity theory of money' (Irving, 1911), which means the mortgage payment rates and the central bank interest rates moves correlatively and positively. The mortgage payment rates increase in order to against the irrational rise of inflation causes referred to the fractional-reserve banking system. The result also confirms the mortgage payment rate is influenced by interest rate positively and significantly in China, consisted with Gan et al. (2012).

After adding the instrumental variables (IR and CPI), the investigation found that the coefficient of the mortgage payment rate increases to -244.4, and the coefficient of the income increases to 79.02 (Table 4.5 GMM_Fixed). These results reject the general hypotheses of economic fundamentals (chapter 4.3.1) based on the more reasonable results. Thus, IR and CPI are the valuable instruments for the endogenous variable of MR.

Based on Hausman tests, the investigation rejects the null hypothesis which refers to p-value as zero. This means the regression has a presence of endogenous variables. The Sargan test of the instrumental variables suggests that the null hypothesis is accepted, whereby the instrumental variables are not relative to the error of regression, with a p-value of 0.9. The endogenous test suggests that the instrumental variables are relative to endogenous variables, referring to the p-value being close to 0. Meanwhile, the results of the 2SLS estimator are similar to GMM estimator. As there is heteroscedasticity in the model, the GMM model is more efficient than the 2SLS model. The mortgage payment rates influence the house price significantly and positively. This result is similar to that of the previous study (Kohn and Bryant, 2010), in which the result is satisfactory for the economic theory. Moreover, the level of inflation rate affects the mortgage payment rates in the economic theory (Miles, 2008). According to the changes in the central bank interest rate (IR), the demand for investment changes is leading to the variation of mortgage payment rates (Shiller, 2007). Thus, H2 is rejected. This means the increase of mortgage payment rates decreases house prices. Moreover, the central bank interest rate and inflation rate (CPI) are relative to the mortgage payment rates. This result is similar to the previous studies (Kohn and Bryant, 2010; Li and Chand, 2013; Miles, 2008; Shiller, 2007; Yu, 2010).

Table 4.5 Regression Results Using IV-GMM (OLS and Panel) for House Price Using Mortgage Payment Rates as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + BR_{it} + LR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP + HPI_{it} + logIC_{it}) + b_{jt}MR_{it} + d_1Orien + d_2Region + d_3Year$$

	OLS	2SLS_OLS	GMM_OLS	Fixed	2SLS_Fixed	GMM_Fixed
Size	0.055*** (14.14)	0.055*** (14.12)	0.055*** (13.07)	0.062*** (16.58)	0.062*** (16.57)	0.062*** (16.57)
Floor_level	21.70*** (8.52)	21.69*** (8.52)	21.57*** (8.17)	22.41*** (9.29)	22.40*** (9.28)	22.40*** (9.28)
Floor_level^2	-0.316*** (-5.63)	-0.316*** (-5.63)	-0.315*** (-6.66)	-0.304*** (-5.72)	-0.304*** (-5.73)	-0.304*** (-5.73)
Bedroom_nums	-2.101*** (-7.67)	-2.101*** (-7.68)	-2.101*** (-8.28)	-2.63*** (-10.08)	-2.63*** (-10.08)	-2.63*** (-10.08)
Livingroom_nums	0.164 (0.55)	0.165 (0.56)	0.145 (0.48)	0.447 (1.60)	0.447 (1.60)	0.447 (1.60)
House_planning_permissions	118.2*** (14.54)	118.3*** (14.55)	118.0*** (12.57)	118.0*** (15.31)	118.0*** (15.32)	118.0*** (15.32)
Floor*House_permissions	-5.495*** (-8.78)	-5.493*** (-8.78)	-5.462*** (-8.30)	-5.594*** (-9.43)	-5.590*** (-9.43)	-5.590*** (-9.43)
Floor^2*House_permissions	0.082*** (5.90)	0.082*** (5.91)	0.081*** (6.90)	0.078*** (5.95)	0.078*** (5.96)	0.078*** (5.96)
House_price_index	0.201*** (9.46)	0.200*** (9.39)	0.202*** (8.79)	0.193*** (9.62)	0.192*** (9.55)	0.192*** (9.55)
Mortgage_payment_rate	-292.0*** (-9.58)	-254.4*** (-8.28)	-252.9*** (-14.06)	-278.7*** (-9.70)	-244.4*** (-8.44)	-244.4*** (-8.44)
Income	77.10*** (35.48)	76.70*** (35.31)	76.46*** (53.31)	79.38*** (38.70)	79.02*** (38.52)	79.02*** (38.52)
North & South	2.32*** (6.25)	2.33*** (6.28)	2.33*** (4.74)	2.48*** (7.01)	2.49*** (7.03)	2.49*** (7.03)
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-809.2*** (-27.99)	-809.9*** (-28.02)	-808.3*** (-22.36)	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)
N	17143	17143	17143	17143	17143	17143
R-square	0.43	0.43	0.43	0.43	0.43	0.43
Instrumented		MR			MR	
Instruments		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI IC NS IR CPI			AS FR FR2 BR LR HPP FRHPP FR2HPP HPI IC NS IR CPI	
Breusch-Pagan test p-value	9.66 0					
Breusch-Godfrey LM test p-value	130.6 0					
Wooldridge test p-value				0.67 0.45		
Likelihood-ratio test p-value				3999 0		
Friedman's test p-value				264.5 0		
Hausman test p-value		91.26 0			85.7 0	
Sargan test p-value		0.24 0.63			0.03 0.9	
Endogenous test p-value		513003 0			170000 0	

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation, IR=central bank interest rate, CPI= consumer price index.

This investigation estimates an IV-GMM regression with endogenous variables of MR and IC (Table 4.6, Table 4.7, Table 4.8 and Table 4.9). Moreover, this investigation made each column for GMM regression with instrumental variables of IR CPI GDP, IR CPI MS, IR CPI GR and IR CPI GE, respectively. The results provide that the central bank interest rates (IR) significantly influence the income (IC) positively, which p-values of IR are 0. Thus, the hypothesis H11 is rejected. The inflation (CPI) influences the income (IC) negatively and significantly, which p-values of CPI are below 0.05 (Table A.16, Table A.23, Table A.30, Table A.37 and Table A.44). The hypothesis H12 is rejected. The results provide that the income is increased by 1.32% when the central bank interest rates increase by 100% (Table A.16). The income is decreased by 0.84% when there is an increase of CPI by 100% (Table A.16). This means the adjustments of central bank interest rates affect the employees' living standards referred to the prices of goods. These results are similar to Irving (1911), which provides that monetary policy be relative to people's financial station. Meanwhile, this result confirms that of Horioka and Wan (2007). It implicates that the real interest rate has a significant positive impact on the household income in Beijing. Because the mortgage loans employed to finance housing purchases, which may disconnect house prices from the household-income fundamental. After adding the instrumental variables (IR CPI and GRP), the investigation found that the coefficients of income are increased by 4.6% (Table 4.8 GMM). This result rejects H1, which means the income increases the property prices more influentially in IV-GMM model and is in line with Shen and Liu (2004). Thus, IR and CPI are the valuable instruments for the endogenous variable of IC.

This investigation found that total investment in fixed assets in the whole country (IFA) (Table A.23), money supply (MS) (Table A.30), local government general budgetary revenue (GR) (Table A.37) and local government general budgetary expenditure (GE) (Table A.44) influence mortgage payment rates significantly and positively. The investment in fixed assets affects the mortgage payment rates by 0.35% significantly, which p-value of IFA is 0. Thus, the hypothesis H13 is rejected. When there is an increase in money supply by 100%, the mortgage payment rates will be increased by 0.138% significantly which p-value of MS is 0. The hypothesis H14 is rejected. If the local government general budgetary revenue increases by 100%, the mortgage payment rates will be increased by 0.163% significantly which p-value of GR is below 0.05. The hypothesis H15 is rejected. The mortgage payment rates will be increased by 0.163% significantly when the local government general budgetary expenditure increases by 100%, which p-value of GE is 0. The hypothesis H16 is rejected.

Based on these results, IFA and GE influence mortgage payment rates positively, which is in line with the theory of ‘conventional wisdom’ (Galbraith, 1958). The results also are in line with Taylor (2000), who provide the instruments of fiscal policy change aggregate demand and influence the monetary policy indirectly in China. However, the results, which MS and GR influence mortgage payment rates positively is contrary to the ‘conventional wisdom’ (Galbraith, 1958) and the ‘quantity theory of money’ (Irving, 1911). The reason of that may be referred to China’s rapid economic growth. As the good condition of economic growth, the increasing government revenue cannot restrain the demand for investments in the housing market. The increase of government revenue means upward pressure on mortgage payment rates. Though the money supply increases, the aggregate demand for GDP is increasing rapidly so that exceed the amount of money supply, caused the increase of interest rate.

Based on Hausman test ($p<0.05$), Sargan test ($p>0.05$) and endogenous test ($p<0.05$), the model is efficient. After adding the instrumental variables (IFA, MS, GR and GE respectively) in the different models, the investigation found that the coefficients of mortgage payment rates are increased to -247.5, -261.8, -252.3 and -253.7 respectively (Table 4.8 GMM and Table 4.9 GMM). This result rejects H2, which means the mortgage payment rates influence property prices negatively and significantly in the more efficient model of IV-GMM and is consistent with Li and Chand (2013), who provide the mortgage payment rate influence China’s urban house prices negatively from 1998 to 2009. Thus, IFA MS GR and GE are the valuable instruments for the endogenous variable of MR.

Table 4.6 Regression Results Using IV-GMM (OLS) for House Price Using Mortgage Payment Rates and Income as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + BR_{it} + LR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * HPP + HPI_{it}) + b_{jt}(MR_{it} + logIC_{it}) + d_1 Orien + d_2 Region + d_3 Year$$

	OLS	2SLS	GMM	2SLS	GMM
Size	0.0548*** (14.14)	0.0547*** (14.10)	0.0547*** (13.00)	0.0547*** (14.11)	0.0549*** (13.05)
Floor_level	21.70*** (8.52)	21.78*** (8.56)	21.75*** (8.25)	21.73*** (8.54)	21.65*** (8.20)
Floor_level^2	-0.316*** (-5.63)	-0.319*** (-5.67)	-0.318*** (-6.75)	-0.317*** (-5.65)	-0.316*** (-6.70)
Bedroom_nums	-2.101*** (-7.67)	-2.086*** (-7.62)	-2.085*** (-8.21)	-2.095*** (-7.65)	-2.094*** (-8.25)
Livingroom_nums	0.164 (0.55)	0.160 (0.54)	0.154 (0.51)	0.163 (0.55)	0.148 (0.49)
House_planning_permissions	118.2*** (14.54)	110.4*** (13.54)	110.3*** (11.79)	115.0*** (13.99)	114.8*** (12.30)
Floor*House_permissions	-5.495*** (-8.78)	-5.516*** (-8.81)	-5.508*** (-8.37)	-5.502*** (-8.79)	-5.483*** (-8.33)
Floor^2*House_permissions	0.0815*** (5.90)	0.0821*** (5.95)	0.0820*** (6.99)	0.0818*** (5.92)	0.0815*** (6.94)
House_price_index	0.201*** (9.46)	0.198*** (9.31)	0.199*** (8.65)	0.199*** (9.35)	0.201*** (8.77)
Mortgage_payment_rate	-292.0*** (-9.58)	-260.3*** (-8.47)	-260.0*** (-14.40)	-256.9*** (-8.34)	-256.0*** (-14.16)
Income	77.10*** (35.48)	80.67*** (36.71)	80.62*** (58.83)	78.33*** (34.57)	78.24*** (57.23)
North & South	2.318*** (6.25)	2.324*** (6.27)	2.326*** (4.73)	2.326*** (6.28)	2.330*** (4.74)
Time Effect	Yes	Yes	Yes	Yes	Yes
Constant	-809.2*** (-27.99)	-796.1*** (-27.52)	-795.6*** (-22.03)	-804.2*** (-27.74)	-802.9*** (-22.27)
N	17143	17143	17143	17143	17143
R-square	0.43	0.43	0.43	0.43	0.43
Instrumented		MR IC			
Instruments		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI GRP		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI IFA	
Breusch-Pagan test p-value	9.66 0				
Breusch-Godfrey LM test p-value	130.6 0				
Hausman test p-value		274 0		143.8 0	
Sargan test p-value		0.02 0.9		0.12 0.73	
Endogenous test p-value		MR 353266 IC 259215 0		MR 380600 IC 69458 0	

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation, IR=central bank interest rate, CPI= consumer price index, GRP=gross regional product, IFA=total investment in fixed assets in the whole country, MS=money supply, GR=local governments general budgetary revenue, GE=local governments general budgetary expenditure.

Table 4.7 Regression Results Using IV-GMM (OLS) for House Price Using Mortgage Payment Rates and Income as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + BR_{it} + LR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP + HPI_{it}) + b_{it}(MR_{it} + logIC_{it}) + d_1 Orien + d_2 Region + d_3 Year$$

	2SLS	GMM	2SLS	GMM	2SLS	GMM
Size	0.0545*** (14.04)	0.0541*** (12.84)	0.0546*** (14.09)	0.0546*** (12.97)	0.0546*** (14.08)	0.0546*** (12.96)
Floor_level	21.97*** (8.62)	22.10*** (8.38)	21.82*** (8.57)	21.82*** (8.27)	21.84*** (8.58)	21.85*** (8.29)
Floor_level^2	-0.323*** (-5.75)	-0.325*** (-6.93)	-0.319*** (-5.69)	-0.319*** (-6.78)	-0.320*** (-5.70)	-0.320*** (-6.80)
Bedroom_nums	-2.055*** (-7.50)	-2.056*** (-8.09)	-2.080*** (-7.60)	-2.080*** (-8.19)	-2.077*** (-7.59)	-2.077*** (-8.18)
Livingroom_nums	0.150 (0.50)	0.174 (0.57)	0.158 (0.53)	0.158 (0.52)	0.157 (0.53)	0.160 (0.53)
House_planning_permissions	94.94*** (11.54)	95.24*** (10.17)	107.7*** (13.20)	107.7*** (11.52)	105.9*** (12.97)	106.0*** (11.37)
Floor*House_permissions	-5.561*** (-8.88)	-5.596*** (-8.51)	-5.524*** (-8.83)	-5.524*** (-8.40)	-5.529*** (-8.83)	-5.533*** (-8.41)
Floor^2*House_permissions	0.0832*** (6.02)	0.0838*** (7.17)	0.0823*** (5.96)	0.0823*** (7.03)	0.0824*** (5.97)	0.0825*** (7.04)
House_price_index	0.195*** (9.14)	0.191*** (8.31)	0.197*** (9.28)	0.197*** (8.61)	0.197*** (9.26)	0.197*** (8.57)
Mortgage_payment_rate	-272.0*** (-8.85)	-273.7*** (-15.06)	-262.4*** (-8.54)	-262.4*** (-14.52)	-263.7*** (-8.58)	-263.9*** (-14.60)
Income	88.49*** (39.23)	88.75*** (62.25)	82.04*** (37.22)	82.04*** (61.24)	82.93*** (37.51)	82.96*** (61.83)
North & South	2.320*** (6.26)	2.312*** (4.70)	2.324*** (6.27)	2.324*** (4.72)	2.323*** (6.27)	2.322*** (4.72)
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-768.9*** (-26.51)	-770.8*** (-21.35)	-791.3*** (-27.35)	-791.3*** (-21.91)	-788.2*** (-27.23)	-788.5*** (-21.87)
N	17143	17143	17143	17143	17143	17143
R-square	0.43	0.43	0.43	0.43	0.43	0.43
Instrumented	MR IC					
Instruments	AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI MS		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI GR		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI GE	
Hausman test p-value	398.6 0		313.8 0		316.6 0	
Sargan test p-value	0.34 0.56		0.21 0.99		0.01 0.94	
Endogenous test p-value	MR 334158 IC 72924 0		MR 350513 IC 199022 0		MR 347080 IC 163986 0	

AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation, IR=central bank interest rate, CPI= consumer price index, GRP=gross regional product, IFA=total investment in fixed assets in the whole country, MS=money supply, GR=local governments general budgetary revenue, GE=local governments general budgetary expenditure.

Table 4.8 Regression Results Using IV-GMM (Panel) for House Price Using Mortgage Payment Rates and Income as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + BR_{it} + LR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP + HPI_{it}) + b_{jt}(MR_{it} + logIC_{it}) + d_1 Orien + d_2 Region + d_3 Year$$

	Fixed	**2SLS**	**GMM**	**2SLS**	**GMM**
Size	0.0617*** (16.58)	0.0616*** (16.56)	0.0616*** (16.56)	0.0616*** (16.56)	0.0616*** (16.56)
Floor_level	22.41*** (9.29)	22.50*** (9.33)	22.50*** (9.33)	22.45*** (9.31)	22.45*** (9.31)
Floor_level^2	-0.304*** (-5.72)	-0.306*** (-5.77)	-0.306*** (-5.77)	-0.305*** (-5.75)	-0.305*** (-5.75)
Bedroom_nums	-2.630*** (-10.08)	-2.619*** (-10.03)	-2.619*** (-10.03)	-2.624*** (-10.05)	-2.624*** (-10.05)
Livingroom_nums	0.447 (1.60)	0.442 (1.58)	0.442 (1.58)	0.445 (1.59)	0.445 (1.59)
House_planning_permissions	118.0*** (15.31)	110.1*** (14.25)	110.1*** (14.25)	114.0*** (14.62)	114.0*** (14.62)
Floor*House_permissions	-5.594*** (-9.43)	-5.615*** (-9.47)	-5.615*** (-9.47)	-5.603*** (-9.45)	-5.603*** (-9.45)
Floor^2*House_permissions	0.0777*** (5.95)	0.0783*** (6.00)	0.0783*** (6.00)	0.0780*** (5.98)	0.0780*** (5.98)
House_price_index	0.193*** (9.62)	0.190*** (9.46)	0.190*** (9.46)	0.191*** (9.51)	0.191*** (9.51)
Mortgage_payment_rate	-278.7*** (-9.70)	-250.4*** (-8.64)	-250.4*** (-8.64)	-247.5*** (-8.52)	-247.5*** (-8.52)
Income	79.38*** (38.70)	83.03*** (40.02)	83.03*** (40.02)	81.09*** (37.89)	81.09*** (37.89)
North & South	2.478*** (7.01)	2.486*** (7.03)	2.486*** (7.03)	2.487*** (7.03)	2.487*** (7.03)
Time Effect	Yes	Yes	Yes	Yes	Yes
Constant	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)
N	17143	17143	17143	17143	17143
Instrumented		MR IC			
Instruments		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI GRP		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI IFA	
Wooldridge test p-value	0.67 0.45				
Likelihood-ratio test p-value	3999 0				
Friedman's test p-value	264.5 0				
Hausman test p-value		291.5 0		151.4 0	
Sargan test p-value		0.3 0.59		0.13 0.72	
Endogenous test p-value		17000 0		16000 0	

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation, IR=central bank interest rate, CPI= consumer price index, GRP=gross regional product, IFA=total investment in fixed assets in the whole country, MS=money supply, GR=local governments general budgetary revenue, GE=local governments general budgetary expenditure.

Table 4.9 Regression Results Using IV-GMM (Panel) for House Price Using Mortgage Payment Rates and Income as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + BR_{it} + LR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP + HPI_{it}) + b_{jt}(MR_{it} + logIC_{it}) + d_1 Orien + d_2 Region + d_3 Year$$

	2SLS	**GMM**	**2SLS**	**GMM**	**2SLS**	**GMM**
Size	0.0616*** (16.54)	0.0616*** (16.54)	0.0616*** (16.56)	0.0616*** (16.56)	0.0616*** (16.56)	0.0616*** (16.56)
Floor_level	22.69*** (9.40)	22.69*** (9.40)	22.53*** (9.34)	22.53*** (9.34)	22.56*** (9.35)	22.56*** (9.35)
Floor_level^2	-0.311*** (-5.85)	-0.311*** (-5.85)	-0.307*** (-5.79)	-0.307*** (-5.79)	-0.307*** (-5.80)	-0.307*** (-5.80)
Bedroom_nums	-2.597*** (-9.94)	-2.597*** (-9.94)	-2.615*** (-10.02)	-2.615*** (-10.02)	-2.612*** (-10.01)	-2.612*** (-10.01)
Livingroom_nums	0.433 (1.54)	0.433 (1.54)	0.441 (1.57)	0.441 (1.57)	0.439 (1.57)	0.439 (1.57)
House_planning_permissions	95.20*** (12.21)	95.20*** (12.21)	107.6*** (13.90)	107.6*** (13.90)	105.8*** (13.66)	105.8*** (13.66)
Floor*House_permissions	-5.662*** (-9.54)	-5.662*** (-9.54)	-5.623*** (-9.48)	-5.623*** (-9.48)	-5.629*** (-9.49)	-5.629*** (-9.49)
Floor^2*House_permissions	0.0794*** (6.08)	0.0794*** (6.08)	0.0785*** (6.02)	0.0785*** (6.02)	0.0786*** (6.03)	0.0786*** (6.03)
House_price_index	0.187*** (9.29)	0.187*** (9.29)	0.189*** (9.43)	0.189*** (9.43)	0.189*** (9.41)	0.189*** (9.41)
Mortgage_payment_rate	-261.8*** (-9.03)	-261.8*** (-9.03)	-252.3*** (-8.71)	-252.3*** (-8.71)	-253.7*** (-8.75)	-253.7*** (-8.75)
Income	90.61*** (42.54)	90.61*** (42.54)	84.33*** (40.51)	84.33*** (40.51)	85.23*** (40.83)	85.23*** (40.83)
North & South	2.481*** (7.01)	2.481*** (7.01)	2.485*** (7.02)	2.485*** (7.02)	2.484*** (7.02)	2.484*** (7.02)
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)
N	17143	17143	17143	17143	17143	17143
Instrumented	MR IC					
Instruments	AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI MS		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI GR		AS FR FR2 BR LR HPP FRHPP FR2HPP HPI NS IR CPI GE	
Hausman test p-value	424.6 0		330.4 0		337.6 0	
Sargan test p-value	1.61 0.2		0.45 0.5		0.57 0.45	
Endogenous test p-value	16000 0		17000 0		17000 0	

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation, IR=central bank interest rate, CPI= consumer price index, GRP=gross regional product, IFA=total investment in fixed assets in the whole country, MS=money supply, GR=local governments general budgetary revenue, GE=local governments general budgetary expenditure.

The factor of HPP*Floor, which represents the demand for property in this research. In Table 4.10, it is suggested that HPP*Floor is an inverse U-shape factor relative to property prices.

Referring to the housing demand (HPP*Floor), total investment in fixed assets in the whole country (IFA) influences house demand significantly and negatively which p-value of IFA is 0; local government general budgetary revenue (GR) influence house demand negatively and significantly as well which p-value of GR is 0 (Table A.51). Thus, the hypothesis H17 and H18 are rejected. These results provide the investment in fixed assets stimulate the housing demand, which is in line with the previous study (Naylor, 1967) and confirms the conventional wisdom (Galbraith, 1958). The local government general budgetary revenue (GR) decreases the housing demand, which is in line with Naylor (1967). This is in line with Koss and Shi (2018), who mentioned that the central government policies, such as “freeze” in transactions, the purchase restrictions and increased land supplies, cannot be regarded as these measures have changed the fundamentals of the residential housing market, particularly with regards to damping the speculative fervour. This is because these policies curbed the house prices in short-term but did not correct the fundamental mismatch in the market between supply and demand or cool the enthusiasm of property speculators in the over-heated cities. After adding the instrumental variables (IFA and GR), the investigation found that the coefficient of housing demand is decreased to -6.557 (Table 4.10 GMM_Fixed). This result implicates that the house price could be decreased through restrain investments and increase government revenue indirectly. Because investments and government revenue decreased the demand for houses.

Through the analysis, the results provide that HPP has a higher correlation with investment in fixed assets (IFA) and government revenue (GR). In order to satisfy the valid instrumental variables, the test of correlation between instrumental variables and endogeneity is applied, which p-value is zero. On the other hand, the Sargan test of the instrumental variables provides that the null hypothesis is accepted. Thus, all the instrumental variables are not relative to regression error, based on the p-value of which is 0.89. The Hausman test shows the regression has a presence of the endogenous variables, based on p-value is zero. The investigation finds that the coefficients of floor level, house price index, income and orientation factor increase after adding the instrumental variables. As the model is efficient, H3 is rejected, which means the demand for property increase the value of the house. This is similar to the previous studies (Kohn and Bryant, 2010; Case and Shiller, 2003; Li et al., 2018) that suggest house demand caused house price volatility in China (Li et al., 2018).

Table 4.10 Regression Results Using IV-GMM (OLS and Panel) for House Price Using House Planning Permissions as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + BR_{it} + LR_{it} + HPI_{it} + MR_{it} + logIC_{it}) \\ + b_{jt}\left(logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP\right) + d_1 Orien + d_2 Region + d_3 Year$$

	OLS	**2SLS_OLS**	**GMM_OLS**	**Fixed**	**2SLS_Fixed**	**GMM_Fixed**
Size	0.0548*** (14.14)	0.0514*** (13.00)	0.0530*** (12.54)	0.0617*** (16.58)	0.0587*** (15.45)	0.0587*** (15.45)
Floor_level	21.70*** (8.52)	25.58*** (8.41)	25.77*** (9.66)	22.41*** (9.29)	26.34*** (9.12)	26.34*** (9.12)
Floor_level^2	-0.316*** (-5.63)	-0.430*** (-6.25)	-0.437*** (-8.90)	-0.304*** (-5.72)	-0.409*** (-6.28)	-0.409*** (-6.28)
Bedroom_nums	-2.101*** (-7.67)	-1.936*** (-6.94)	-1.945*** (-7.48)	-2.630*** (-10.08)	-2.489*** (-9.35)	-2.489*** (-9.35)
Livingroom_nums	0.164 (0.55)	0.114 (0.38)	-0.00257 (-0.01)	0.447 (1.60)	0.399 (1.40)	0.399 (1.40)
House_planning_permissions	118.2*** (14.54)	-0.400 (-0.03)	-4.987 (-0.45)	118.0*** (15.31)	3.930 (0.32)	3.930 (0.32)
Floor*House_permissions	-5.495*** (-8.78)	-6.446*** (-8.62)	-6.491*** (-9.74)	-5.594*** (-9.43)	-6.557*** (-9.23)	-6.557*** (-9.23)
Floor^2*House_permissions	0.0815*** (5.90)	0.110*** (6.48)	0.111*** (9.09)	0.0777*** (5.95)	0.103*** (6.46)	0.103*** (6.46)
House_price_index	0.201*** (9.46)	0.249*** (11.33)	0.261*** (10.93)	0.193*** (9.62)	0.239*** (11.53)	0.239*** (11.53)
Mortgage_payment_rate	-292.0*** (-9.58)	-308.5*** (-9.93)	-308.7*** (-15.62)	-278.7*** (-9.70)	-295.1*** (-10.06)	-295.1*** (-10.06)
Income	77.10*** (35.48)	126.5*** (29.72)	127.8*** (51.89)	79.38*** (38.70)	127.5*** (31.72)	127.5*** (31.72)
North & South	2.318*** (6.25)	2.452*** (6.49)	2.602*** (5.39)	2.478*** (7.01)	2.629*** (7.29)	2.629*** (7.29)
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-809.2*** (-27.99)	-563.6*** (-14.57)	-552.9*** (-14.34)	-823.9*** (-29.97)	-823.9*** (-29.97)	-823.9*** (-29.97)
N	17143	17143	17143	17143	17143	17143
R-square	0.43	0.409	0.407	0.46	0.44	0.44
Instrumented		HPP FRHPP FR2HPP			HPP FRHPP FR2HPP	
Instruments		AS FR FR2 BR LR HPI MR IC NS IFA GR IFAFR IFAFR2 GRFR GRFR2			AS FR FR2 BR LR HPI MR IC NS IFA GR IFAFR IFAFR2 GRFR GRFR2	
Breusch-Pagan test p-value	9.66 0					
Breusch-Godfrey LM test p-value	130.6 0					
Wooldridge test p-value				0.67 0.45		
Likelihood-ratio test p-value				3999 0		
Friedman's test p-value				264.5 0		
Hausman test p-value		200 0			212.21 0	
Sargan test p-value		2.89 0.41			0.63 0.89	
Endogenous test p-value		849(HPP) 3686(HPPFR) 5847(HPPFR2) 0			3926.7 0	

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation, IR=central bank interest rate, CPI= consumer price index, IFA=total investment in fixed assets in the whole country, GR=local governments general budgetary revenue.

Referring to the relationship between property characteristics and property prices, the investigation finds that the floor level of a property, the number of bedrooms (BR), and the number of living rooms (LR) influence the property price significantly. The results provide the house orientation (Orien) influence the condition of the bedroom and the condition of living room positively and significantly (Table A.65, Table A.68, Table A.73, Table A.76, Table A.81 and Table A.84). According to the results, the orientation factors of SE NW WE and SW negatively influences the number of bedrooms by 0.174, 0.252, 0.155 and 0.019 respectively and significantly which p-values of these orientation factors are 0. The hypothesis H19 is rejected. The orientation factor of W negatively influences the number of living rooms by 0.225 significantly which p-values of these orientation factors are 0. The hypothesis H20 is rejected. However, the orientation factor of WE affects the number of living rooms positively by 0.048 significantly which p-value of WE is 0. These results are similar to Rosen (1974), which illustrates that the house characteristics influence house prices. The results of this study are in line with Jim and Chen (2009), who suggested that daylight and views from houses are significant factors affecting house prices. After adding the instrumental variables (orientation factors) in different models, the investigation found that the coefficients of BR are decreased to -31.54, -18.95 and -20.68 respectively (Table 4.12 GMM and Table 4.13 GMM). The coefficient of LR is increased to 5.938 (Table 4.14 GMM). These results are in line with Rosen (1974). However, when the investigation considers the factor of floor level with the number of bedrooms, the factor of Bedroom*Floor influences house prices positively and significantly with instruments of SE SW and SW NW by 0.55 and 0.398 respectively. The coefficient of Living_room*Floor increases to 0.617. This means the more bedrooms are facing southeast and southwest or facing southwest and northwest with higher floor level, the higher house price. The more living rooms are facing west or east with higher floor level, the higher house price. Generally, the house facing south and west have more extended daylight, which increases the temperature of the room, so that increase the electrical efficiency. However, the bedrooms facing southwest, southeast or northwest not only keeps daylight but also reduces west sunburn and improves natural ventilation to improve sleeping context. The living room improves west sunburn increasing the whole house temperature so that increase house efficiency. Moreover, the higher floor level of houses, the more efficient daylight and natural ventilation. Thus, this investigation found the more numbers of rooms with proper orientation, the better condition of the room is which has good daylight and better natural ventilation. Therefore, the factors of orientation influences house prices, which rejects H8. This result is never been found in previous studies.

Table 4.11 Regression Results Using IV-GMM (OLS) for House Price Using Bedroom_nums as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + LR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP + HPI_{it} + MR_{it} + logIC_{it}) + b_{jt}(BR_{it} + BRFR_{it}) + d_1 Orien + d_2 Region + d_3 Year$$

	OLS	2SLS	GMM	2SLS	GMM
Size	0.0560*** (14.46)	0.171*** (3.63)	0.203*** (4.18)	0.0473 (0.69)	0.0405 (1.04)
Floor_level	23.11*** (9.03)	15.63*** (3.36)	13.49*** (2.79)	20.91*** (3.00)	29.58*** (5.36)
Floor_level^2	-0.338*** (-6.01)	-0.236*** (-2.96)	-0.208*** (-2.78)	-0.305*** (-2.67)	-0.436*** (-4.89)
Bedroom_nums	0.0619 (0.15)	-16.55** (-2.26)	-21.12*** (-2.71)	-1.643 (-0.27)	-7.941 (1.53)
Bedroom*Floor	-0.103*** (-6.20)	0.170 (1.02)	0.242 (1.42)	0.0411 (0.09)	0.453 (-1.47)
Livingroom_nums	0.363 (1.22)	4.255*** (2.64)	5.371*** (3.23)	-0.0581 (-0.02)	0.0666 (0.04)
House_planning_permissions	121.6*** (14.91)	108.0*** (9.55)	102.9*** (8.21)	116.6*** (6.78)	134.3*** (9.45)
Floor*House_permissions	-5.781*** (-9.20)	-4.171*** (-4.03)	-3.704*** (-3.42)	-5.353*** (-3.83)	-7.090*** (-6.13)
Floor^2*House_permissions	0.0866*** (6.26)	0.0623*** (3.26)	0.0555*** (3.10)	0.0793*** (3.11)	0.109*** (5.30)
House_price_index	0.201*** (9.47)	0.205*** (9.06)	0.202*** (8.36)	0.204*** (9.14)	0.197*** (8.66)
Mortgage_payment_rate	-296.5*** (-9.73)	-296.1*** (-9.16)	-296.5*** (-13.47)	-295.0*** (-9.52)	-294.7*** (-15.47)
Income	77.37*** (35.60)	73.91*** (27.07)	73.31*** (33.26)	77.29*** (30.54)	78.10*** (47.30)
Time Effect	Yes	Yes	Yes	Yes	Yes
Constant	-828.4*** (-28.45)	-734.9*** (-13.06)	-705.1*** (-11.40)	-801.1*** (-9.38)	-902.3*** (-13.01)
N	17143	17143	17143	17143	17143
Instrumented		BR BRFR			
Instruments		AS FR FR2 LR HPP FRHPP FR2HPP HPI MR IC SE NW FRSE FRNW		AS FR FR2 LR HPP FRHPP FR2HPP HPI MR IC NW NE FRNW FRNE	
Breusch-Pagan test p-value	9.22 0				
Breusch-Godfrey LM test p-value	130.6 0				
Hausman test p-value		6.89 0.03		37.96 0	
Sargan test p-value		5.86 0.05		3.22 0.2	
Endogenous test p-value		BR 36.8 BRFR 122.8 0		BR 198.1 BRFR 195.5 0	
** p<0.10 ** p<0.05 *** p<0.01*					
T-statistic are in parenthesis					
AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation.					

Table 4.12 Regression Results Using IV-GMM (Panel) for House Price Using Bedroom_nums as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + LR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP + HPI_{it} + MR_{it} + logIC_{it}) + b_{jt}(BR_{it} + BRFR_{it}) + d_1Orien + d_2Region + d_3Year$$

	Fixed	2SLS	GMM
Size	0.0628*** (16.89)	0.258*** (5.31)	0.258*** (5.31)
Floor_level	23.51*** (9.69)	10.41** (2.17)	10.41** (2.17)
Floor_level^2	-0.321*** (-6.03)	-0.142* (-1.72)	-0.142* (-1.72)
Bedroom_nums	-0.889** (-2.30)	-31.54*** (-3.87)	-31.54*** (-3.87)
Bedroom*Floor	-0.0778*** (-4.93)	0.550*** (2.76)	0.550*** (2.76)
Livingroom_nums	0.628** (2.24)	6.686*** (4.39)	6.686*** (4.39)
House_planning_permissions	121.0*** (15.64)	96.34*** (8.14)	96.34*** (8.14)
Floor*House_permissions	-5.823*** (-9.78)	-3.077*** (-2.89)	-3.077*** (-2.89)
Floor^2*House_permissions	0.0818*** (6.25)	0.0398** (2.00)	0.0398** (2.00)
House_price_index	0.194*** (9.66)	0.201*** (8.39)	0.201*** (8.39)
Mortgage_payment_rate	-283.5*** (-9.86)	-289.5*** (-8.45)	-289.5*** (-8.45)
Income	79.55*** (38.75)	75.27*** (28.11)	75.27*** (28.11)
Time Effect	Yes	Yes	Yes
Constant	-839.6*** (-30.34)	-839.6*** (-30.34)	-839.6*** (-30.34)
N	17143	17143	17143
Instrumented		BR BRFR	
Instruments		AS FR FR2 LR HPP FRHPP FR2HPP HPI MR IC SE SW FRSE FRSW	
Hausman test p-value	669.7 0		
Wooldridge test p-value	0.603 0.467		
Likelihood-ratio test p-value	4011.6 0		
Friedman's test p-value	294.7 0		
Hausman test p-value		24.32 0	
Sargan test p-value		5.85 0.05	
Endogenous test p-value		50.94 0	
** p<0.10 ** p<0.05 *** p<0.01*			
T-statistic are in parenthesis			
AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation.			

Table 4.13 Regression Results Using IV-GMM (Panel) for House Price Using Bedroom_nums as Endogenous Variables

$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + LR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP + HPI_{it} + MR_{it} + logIC_{it}) + b_{jt}(BR_{it} + BRFR_{it}) + d_1Orien + d_2Region + d_3Year$				
	2SLS	**GMM**	**2SLS**	**GMM**
Size	0.195*** (4.23)	0.195*** (4.23)	0.176*** (5.14)	0.176*** (5.14)
Floor_level	16.96*** (4.23)	16.96*** (4.23)	14.19*** (3.34)	14.19*** (3.34)
Floor_level^2	-0.235*** (-3.30)	-0.235*** (-3.30)	-0.192** (-2.57)	-0.192** (-2.57)
Bedroom_nums	-18.95*** (-2.75)	-18.95*** (-2.75)	-20.68*** (-3.36)	-20.68*** (-3.36)
Bedroom*Floor	0.197 (1.27)	0.197 (1.27)	0.398** (2.08)	0.398** (2.08)
Livingroom_nums	4.864*** (3.27)	4.864*** (3.27)	4.048*** (3.69)	4.048*** (3.69)
House_planning_permissions	109.3*** (10.74)	109.3*** (10.74)	103.0*** (9.59)	103.0*** (9.59)
Floor*House_permissions	-4.418*** (-4.91)	-4.418*** (-4.91)	-3.895*** (-4.18)	-3.895*** (-4.18)
Floor^2*House_permissions	0.0610*** (3.56)	0.0610*** (3.56)	0.0518*** (2.91)	0.0518*** (2.91)
House_price_index	0.197*** (9.07)	0.197*** (9.07)	0.199*** (9.17)	0.199*** (9.17)
Mortgage_payment_rate	-288.2*** (-9.27)	-288.2*** (-9.27)	-286.5*** (-9.24)	-286.5*** (-9.24)
Income	76.85*** (31.72)	76.85*** (31.72)	76.92*** (32.77)	76.92*** (32.77)
Time Effect	Yes	Yes	Yes	Yes
Constant	-839.6*** (-30.34)	-839.6*** (-30.34)	-839.6*** (-30.34)	-839.6*** (-30.34)
N	17143	17143	17143	17143
Instrumented	BR BRFR			
Instruments	AS FR FR2 LR HPP FRHPP FR2HPP HPI MR IC SE NW FRSE FRNW		AS FR FR2 LR HPP FRHPP FR2HPP HPI MR IC SW NW FRSW FRNW	
Hausman test p-value	10.02 0.01		13.17 0	
Sargan test p-value	5.29 0.07		4.81 0.09	
Endogenous test p-value	53.94 0		77.92 0	
** p<0.10 ** p<0.05 *** p<0.01*				
T-statistic are in parenthesis				
AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation.				

Table 4.14 Regression Results Using IV-GMM (OLS) for House Price Using Livingroom_nums as Endogenous Variables

$$P_{it} = \alpha_0 + b_{it}(AS_{it} + FR_{it} + FR_{it}^2 + BR_{it} + logHPP_{it} + FR_{it} * logHPP + FR_{it}^2 * logHPP + HPI_{it} + MR_{it} + logIC_{it}) + b_{jt}(LR_{it} + LRFR_{it}) + d_1 Orien + d_2 Region + d_3 Year$$

	OLS	2SLS	GMM
Size	0.0551*** (14.23)	0.0109 (0.41)	0.0141 (0.73)
Floor_level	22.69*** (8.88)	13.32** (2.55)	13.95*** (3.01)
Floor_level^2	-0.331*** (-5.89)	-0.211** (-2.50)	-0.219*** (-2.73)
Bedroom_nums	-1.808*** (-6.70)	-7.342** (-2.31)	-6.976*** (-3.07)
Livingroom_nums	3.165*** (5.68)	6.879 (1.05)	5.938*** (1.19)
Livingroom_nums*Floor	-0.146*** (-6.09)	0.634* (1.80)	0.617** (2.35)
House_planning_permissions	120.5*** (14.80)	99.40*** (7.32)	101.5*** (7.80)
Floor*House_permissions	-5.696*** (-9.08)	-3.761*** (-3.27)	-3.909*** (-3.69)
Floor^2*House_permissions	0.0853*** (6.17)	0.0575*** (2.83)	0.0594*** (3.04)
House_price_index	0.203*** (9.55)	0.219*** (8.42)	0.216*** (8.12)
Mortgage_ payment_rate	-295.7*** (-9.70)	-290.6*** (-8.33)	-291.7*** (-12.42)
Income	77.20*** (35.53)	75.58*** (28.73)	75.76*** (38.69)
Time Effect	Yes	Yes	Yes
Constant	-822.7*** (-28.34)	-715.1*** (-12.00)	-724.1*** (-13.03)
N	17143	17143	17143
Instrumented		LR LRFR	
Instruments		AS FR FR2 LR HPP FRHPP FR2HPP HPI MR IC W WE FRW FRWE	
Breusch-Pagan test p-value	9.68 0		
Breusch-Godfrey LM test p-value	130.8 0		
Hausman test p-value		6.45 0.04	
Sargan test p-value		2.02 0.36	
Endogenous test p-value		LR 12.7 LRFR 8.08 0	
** p<0.10 ** p<0.05 *** p<0.01*			
T-statistic are in parenthesis			
AS=the size of property, FR=the floor level of property located, BR=number of bedroom, LR=number of living room, HPP=floor space under construction of Beijing land, HPI=house price index, MR=monthly mortgage payment rates, IC=Income, Orien=dummy for property orientation.			

4.6 Conclusion

This chapter investigates the empirical relationship between house price, economic fundamental effects and house characteristics effects via the panel model and IV-GMM. Specifically, the results indicate that the economic factors have influenced the house price based on the economic theories (Cheng et al., 2014; Galbraith, 1958; Irving, 1911; Maisel, 1963; Naylor, 1967). The house characteristics have influenced the property price significantly, which indicates that consumer behaviour is an essential aspect of the housing market (Rosen, 1979). The results have rejected the hypotheses that economic fundamentals and house characteristics are exogenous variables on property price. Therefore, this study provides innovative evidence that the economic fundamentals and the house characteristics are essential factors in the Chinese housing market. This result is supported by a number of previous studies in western country (Jim and Chen, 2009; Larraz and Alfaro, 2008; Malpezzi, 2002; Meen, 1996; Oikarinen, 2006; Rosen, 1974) and in China (Gan et al., 2012; Horioka and Wan, 2007; Hui and Gu, 2009; Li and Chand, 2013; Li et al., 2018; Shen and Liu, 2004; Taylor, 2000; Wong et al., 2005; Yu, 2010; Zhang and Yi, 2017).

Regarding the house characteristics, house size is leading to an increase in house prices which is in line with Zhang and Yi (2017) who found there is a positive relationship between house price and size of living area in Beijing. This result is also similar to Fang et al. (2016) who provide that despite the critical financial burdens afforded by the households, the home size is spacious which is more than the standards of most metropolitan areas in the world. It implies that home size in Beijing influences the housing demand in terms of China's characterised consumer behaviour of households who prefer to buy larger-size house. There is a significant positive relationship between house prices by floor level and negative relationship on property prices with FR^2. This result is similar to a previous study by Wong et al. (2005). This means the floor level influences the house price positively from the lower floor level to the middle floor level in a tall building. However, from the middle floor level to the upper floor level, the floor level influences house prices negatively. It implies that the household in Beijing preferred to buy a similar condition house with the lower price. The number of bedrooms has a significant negative influence on property prices. This situation may be based on privacy. According to Fahey (2016), one-bedroom rents are more expensive than two-bedroom rents. In terms of the house orientation, the north and south factor is significant and positive, which means that houses facing north and south have an increased price of 2.48%. This result is found in the previous studies (Fang et al., 2016 and Zhang and

Yi, 2017). This is because houses facing north and south have better natural ventilation and more daylight, which improves the natural quality of a house and its energy efficiency. However, it is similar to Jim and Chen (2009) who suggested that daylight and views from houses are significant factors affecting house price.

Regarding the economic fundamentals, the mortgage down payment has a significant negative influence on property prices. This result is in line with Fang et al. (2016), Yu (2010) and Li and Chand (2013), who provided the mortgage down payment influence China's urban house prices negatively by data between 1998 and 2009. Thus, it is suggested that the high levels of down payments in China should be kept which can not only reduce the risk of household default for the bank but also decline the housing demand significantly. The average income of citizens influences house price significantly and positively. This result is in line with Hui and Gu (2009) and Shen and Liu (2004), who provide income significantly influence the house price in China. Housing assets have been a significant part of household wealth in China. The housing assets accounted for 66% of household wealth in China in 2016 (Liu and Xiong, 2018). Therefore, it is recommended that the demand for purchasing power in the Chinese housing market is influenced by the household incomes. The demand quantity of properties (Floor*House_permissions) has an inverse U-shape relationship with house prices. This result is not similar to Li et al. (2018), who provide the ratios of residential floor space under construction to floor space increase house price each year after 2004. This is because the thesis improved the method of calculating house demand, which is more flexible with an inverse U-shape relationship to explore the house price and house demand. Although some studies were undertaken in different countries, all of the results corresponded with economic theory. Based on such findings, economic factors have a significant influence on property prices in Beijing.

Baltagi (2001) provides that employing the values of the other variable regressors as instruments can increase consistency and efficiency of the model. The IV-GMM model employed the instrumental variables to improve the efficiency of the model. Meanwhile, the IV-GMM method restricted unobserved heterogeneity and limited the consistency of the dependent variable. To deal with this, the independent variables employed in this investigation refer to the IV-GMM method. The result provides that the central bank interest rates (IR) significantly influence the income (IC) positively and the inflation (CPI) influences the income (IC) negatively and significantly. This result confirms that of Horioka and Wan (2007), who found the real interest rate has a significant positive impact on the household income in China between 1995 and 2004. It implies that the central bank interest rates and inflation influences the house price in Beijing indirectly which is in line with Koss and Shi (2018).

Regarding the fiscal factors which are treated as the instruments to the variable of mortgage down payments, the results provide that the investment in fixed assets (IFA) affect the mortgage payment rates positively and significantly. If the local government general budgetary revenue (GR) increases, the mortgage payment rates will be increased significantly. The mortgage payment rates will be increased significantly when the local government general budgetary expenditure (GE) increases. Based on these results, IFA and GE influence mortgage payment rates positively, which is in line with the theory of 'conventional wisdom' (Galbraith, 1958). The results also are in line with Taylor (2000), who provide the instruments of fiscal policy change aggregate demand and influence the monetary policy indirectly in China. However, the result, which money supply (MS) and GR influence mortgage payment rates positively, is contrary to the 'conventional wisdom' (Galbraith, 1958) and the 'quantity theory of money' (Irving, 1911). The reason for that may be referred to the Budget Law. The local governments expend the fiscal capacity by non-budgetary funding sources such as land sales (Liu and Xiong, 2018). Therefore, the increasing government revenue cannot restrain the demand for investments in the housing market. Regarding China's "Local Government Financing Platform" (LGFP), the increase of government revenue means upward pressure on mortgage payment rates. Though the money supply increases, the aggregate demand for GDP is increasing rapidly so that exceed the amount of money supply, caused the increase of interest rate. Therefore, when the central government tightens monetary policy to limit debt accumulation by local governments, LGFP has been regulated. Accordingly, the fiscal factors and interest rate influence the house prices in Beijing indirectly.

Furthermore, the results provide the house orientation (Orien) influences the condition of the bedroom and the condition of living room positively and significantly. The orientation factors of SE NW WE and SW negatively influence the number of bedrooms respectively and significantly. The orientation factor of W negatively influences the number of the living rooms significantly. The orientation factor of WE affects the number of living rooms positively and significantly. The results of this study are in line with Jim and Chen (2009), who suggested that daylight and views from houses are significant factors affecting house prices. After adding the instrumental variables (orientation factors) in different models, the investigation found that the coefficients of BR are decreased. The coefficient of LR is increased. These results are in line with Rosen (1974). However, when the investigation considers the factor of floor level with number of bedrooms, the factor of Bedroom*Floor influences house prices positively and significantly with instruments of SE SW and SW NW respectively. The coefficient of Living_room*Floor increases. This means the more bedrooms are facing southeast and southwest or facing southwest and northwest with higher floor level, the higher house price. The more living rooms are facing west or east with higher floor level, the higher house price. Generally, the house facing south and west have more extended daylight, which increases the temperature of the room, so that increase the electrical efficiency. However, the bedrooms facing southwest, southeast or northwest not only keeps daylight but also reduces west sunburn and improves natural ventilation to improve sleeping context. The living room improves west sunburn increasing the whole house temperature so that increase house efficiency. Moreover, the higher floor level of houses, the more efficient daylight and natural ventilation. Thus, this investigation found the more numbers of rooms with proper orientation, the better condition of the room is which has good daylight and better natural ventilation. This result provides the orientation of the property influence the property prices indirectly in Beijing.

Regarding IV-GMM methods, the hypotheses are examined by the endogenous test. In the hypotheses, the coefficients of the independent variables are not significant and are individually equal to zero. If the null hypothesis is not rejected, the model is not efficient so that to modify the equation. With regards to the efficient model, the null hypothesis should be rejected so that the independent variables are significant in the general regression. Alternatively, the investigation could reduce the number of non-significant variables to estimate a confining hypothesis. Such estimations yield consistent estimations of the parameters. The coefficients of independent variables are respectable and refer to the restriction for the number of independent variables. According to the test of error terms unrelated to regressors, the hypothesis is rejected, which means that the regressors have endogeneity. With respect to linear instrumental variables regression, this investigation applies and tests the instrumental variables and endogeneity in order to establish IV-GMM models. As there is heteroscedasticity in the model, the GMM model is more efficient than the 2SLS model. This research employs mortgage payment rates, income, house planning permissions, number of bedrooms, number of living room as the endogenous variable respectively. The results of test reject the null hypothesis, indicating that IV-GMM is efficient and appropriate to be employed in the investigation of house prices in Beijing in terms of the relevant factors influencing the house prices indirectly.

In conclusion, this investigation complements the literature that studies the determinants of real estate markets and the economic area. This research is based on the panel model and IV-GMM, which could monitor the process of influencing factors. Defining the endogenous variable through instrumental variables is more detailed in terms of analysing exogenous variables. This investigation factors in a new variable of the orientation of property. This variable has never been analysed in previous studies. Through the panel analysis and GMM model, the results found that the orientation of property has influences on property price directly and indirectly. In addition, this study examines an extended period (2002-2014), which provides a sample of 17,143 property transaction records containing detailed information to examine the whole of Beijing’s core real estate area. It encourages the developer of houses to have a rational house structure in order to have a maximum shareholder value. It also implicates that the regulators of banks and government should monitor the mortgage payment rate, interest rate, government revenue and expenditure in order to deter the irrational increasing house price.

Chapter 5 The Spatial Analysis and Spill-Over Effects of House Price in Beijing

5.1 Introduction

From one decade to 2013, China's house prices increased at an annual nominal rate of 16.4% (**Error! Reference source not found.**). The increases in house price over time and across space has developed a price distribution in most area of China, especially in Beijing (Liu et al., 2016). China's private housing market was developed by the reforms containing land system, property taxes, and access to credit (Chen et al., 2015). In terms of the reform process, economic prosperity and rapid urbanisation have stimulated the demand for housing. Based on **Error! Reference source not found.**, per capita income has grown rapidly at a rate of 31.1% per annum between 2003 and 2013. The rapid increasing per capita income within the boundary regions of urban, which also encourage the development of urbanisation (Li and Chand, 2013). During these ten years, nearly 260 million rural workers migrated to Tier 1 and Tier 2 cities. Therefore, increased demand for housing was accompanied by increased supply as prices and rents increased. There are many previous studies have provided one of driven for rapidly expanding house price is the population in China (Chow et al., 2016; Gong et al., 2015; Li and Chand, 2013; Liu et al., 2016; Zhang et al., 2015; Zhang et al., 2018). The prior studies illustrated that economic fundamentals in China can drive the increase in the long run equilibrium price of house prices, such as building starts (Hanink et al., 2012; Zhang et al., 2018), income (Hui and Gu, 2009; Shen and Liu; 2004), tax (Guo et al., 2012; Li and Chand, 2013; Liu, 2013), unemployment rate (Harris et al., 2013) and central bank interest rate (Li and Chand, 2013; Yu, 2010). However, these studies did not address the spatial effects of the determinates of house prices. Therefore, this chapter investigates spatial analysis to examine house price and its determinates and spill-over effects in Beijng.

The problems in cities are to some extent relaxed with the city planner by the different solutions through the alternative methods in various countries. Evans (1973) mentions that the free market operation causes the urban problems in the UK; however, the town planner could solve these urban problems by executing the allotment of land uses enforcedly. In the United States, predicting the future pattern of land use is the responsibility of city planner, who will decide the optimal distribution of fixed assets investments. Based on the real estate development of China, Beijing is the first city which attempted to implement the operation of the free real estate market. It is valuable to analyse the effects of neighbouring regions on house price in Beijing in terms of predicting the future pattern of house prices in order to response the city planner.

Referred to the previous studies (Giussani and Hadjimatheou, 1991; Meen, 1999), the increasing demand that occurs as a result of migration to regions where house prices are comparably low results in an increase in house prices. The house price difference is caused by information asymmetries suggested that new information referred to the housing market in one area is transported gradually to other submarkets. The spatial analyses of house price in China have been provided by the prior studies (Guo et al., 2012; Li and Chand, 2013; Harris et al., 2013; Liu et al., 2016; Chow et al., 2016; Gong et al., 2016; Shi and Lee, 2017; Zhang et al., 2017; Yang et al., 2018). While the Chinese housing market is significantly different from the other countries' housing market in terms of the development levels. Thus, the spatial autoregressive and spatial error component are essential to be investigated in understanding the spatial spillovers of house prices in China.

In this Chpater, the evidence is found for spatial dependence of house prices: house prices in one region are influenced by the house prices in neighbouring regions, positively and significantly in Beijing. The evidence is found for spatial heterogeneity of house prices across space: house price spill-over is greater in neighbouring regions when neighbouring house prices are increasing than when neighbouring house prices are declining. The evidence is found for spatial spill-over effects of explanatory factors: increases of the average wage, income, tax, urban population and house price of last year increase the house price positively in neighbouring regions; a decrease of unemployment drives down the house prices in neighbouring regions. These factors have spill-over effects across space.

From the theoretical standpoint, these findings are likely to contribute to the theory of "the concentric zone' Burgess (1925) that the information will expand radially from its central place or the city leading to information asymmetries in the surroundings. Consistent with this view, the findings reveal that the house prices in Beijing have a geographical variation and expand radially from CBD. This encourages the city planner of Beijing to simulate the regulation of the United States, which predicts the future pattern of land use in order to decide the optimal distribution of fixed assets investments. The rational distribution of fixed assets effectively averse the unstable house price variation referred to the information asymmetries.

5.1.1 Research Objectives

This empirical chapter investigates the spatial statistics of house prices in Beijing between 2003 and 2013. It examines whether house prices in one region are affected by house prices in neighbouring regions. This investigation also analyses how house prices in one region are affected by unknown characteristics of the neighbouring regions. Moreover, it explores whether the explanatory factors of house prices in one region are affected by explanatory factors of house prices in neighbouring regions. In addition, this chapter investigates the spill-over effects of explanatory factors on house prices. This investigation also examines the partitioning of direct effect and indirect effect from the impacts of the neighbouring factors on house prices. This research aims to overcome the shortcomings of the previous studies by extending the range of examining spatial models, providing reasonable spatial model selection procedures, and employing improved spatial weights to analyse spill-over effects of explanatory factors.

5.1.2 Summary of Findings and Contribution

This investigation finds that house prices in one district and the surrounding districts exists the significance of spatial autocorrelation. The results reveal strong house price spill-overs when the increase in house price, size of building started, average wage, income, tax, and a population of the neighbouring regions is taken into account. The evidence for the disposition effect of house prices in Beijing is based on the below results.

The house price spill-overs in Beijing area exist when there is an increase in the population of the neighbouring regions, significant upper house price spill-overs are detected in terms of increasing house prices in the neighbouring regions. This result is similar to Zhang et al. (2015) and Chow et al. (2016), which means the urban population influence house prices positively and significantly in Beijing. This finding is in line with Alonso (1964), who provides the population is a significant factor in the economic analysis, because the population changes the demand for the number of houses. In the theory of ‘the concentric zone’ (Burgess, 1925), the development of ideal construction of the city expands from its CBD. The workers live near CBD aims to easy access to their work. Thus, the demand for house surrounding CBD is high, which causes the increase in house price. The findings of this analysis are also in line with Burgess’s theory (1925) that the distance from district to CBD influenced the house price significantly and negatively. This encourages the regulators of Beijing housing market to establish the rational distribution of fixed assets effectively deter the unstable house price variation referred to the population changes.

The differences in household income cause changes in residential location and house prices based on the ‘sector theory’ (Hoyt, 1939). This result is in line with Shen and Liu (2004). The income significantly influences the house price in Beijing and changes the distribution of house prices. This investigation provides a similar result to Hoyt’s theory (1939), which the average wage of employees in the real estate market leads to an increase in house price. This finding is also in line with the theory of ‘the concentric zone’ (Burgess, 1925), which presents the high-income group ‘who have escaped from the area of deterioration’ changes the demand of residential location. This encourages the regulators of Beijing housing market to establish the subsidiary CBD in Beijing in order to arrange rational distribution of fixed assets.

Evans (1973) found that there is an equilibrium relationship between the density and revenue of houses in ‘the theory of the supply of space’. Thus, even though there is enough space for construction, the irrational density of buildings leads to lower revenues of the house. Size of building starts, which instead of the supply of houses, influences house prices positively. This result is in line with Hanink et al. (2012) and Zhang et al. (2018) who provide house starts is a potential determination of new construction rate which reflects the supply of housing market in Beijing. However, the result is not very significant. The result is similar to Evans (1973), who suggests a rational space and density of constructions are significant to households. Thus, it encourages the regulators of Beijing housing market to control the building permits and continue updating the policy of construction so that rationally monitor the supply of houses.

The research found the taxes and other charges on principal business of enterprises for real estate development lead to an increase in house price significantly. This result is similar to the previous studies (Li and Chand, 2013; Liu, 2013), which means the taxes and other charges on principal business of enterprises for real estate development influence house prices negatively and significantly in Beijing. Based on the trade-off theory (Evans, 1973), the maximum utility of the household is the objective of the choice of location. The increasing tax added the costs of construction, and then the developers will increase the house selling price so that balance the costs. When the household considers the house price, they will change the location of living so that the patterns of residential location changes. Thus, it encourages the regulators of Beijing housing market to control the tax rates, so that have a rational distribution of constructions.

The results of partitioning analyses are appropriately explaining the effects of surroundings, which can approach the utilities. Because of loss aversion, homeowners who intend to sell their properties will not lower their asking price, even when they see house prices declining in neighbouring regions. Loss aversion reduces the number of transactions in the housing market and, reduces the amount of house price spill-over. Results of this study are similar to previous findings (Genesove and Mayer, 2001; Engelhardt, 2003; Anenberg, 2011) with regards to loss aversion in the housing market. This result is also in line with the previous studies (Yang, Noah, and Shoff, 2015), who show that the results of significant levels of the partitioned indirect effects in the second order are higher than those of the other order neighbours, which are referred to in the complicated estimation process in Spatial Durbin Model. Thus, it is suggested that the regulators of Beijing housing market should monitor the economic factors and population in the different order regions in order to adjust the house prices.

From the theoretical standpoint, these findings are likely to contribute to the theory of "the concentric zone' Burgess (1925) that the information will expand radially from its central place or the city leading to information asymmetries in the surroundings. Consistent with this view, the findings reveal that the house prices in Beijing have a geographical variation and expand radially from CBD. This encourages the city planner of Beijing to simulate the regulation of the United States, which predicts the future pattern of land use in order to decide the optimal distribution of fixed assets investments. The rational distribution of fixed assets effectively averse the unstable house price variation referred to the information asymmetries.

This investigation is the first study to provide the partitioning spill-over effects on house prices based on the regional information asymmetries. In the findings, the significance of the partitioned spill-over effects on urban population and GDP are in the second-order surrounding regions. This result is consistent with and contributed to the 'sector theory' (Hoyt, 1939), which the differences in household income cause the changes of residential location and house prices. Thus, it is valuable information for the regulators of real estate market. Because the appropriate distribution of submarket of CBD reduces the degree of income differences, so that decreases the geographical house price variation.

This chapter extends previous research in terms of the data sample and independent variables used, and by combining methods used in economics and geography. In particular, this investigation examines 15 regions of Beijing over an extended period (2002-2014). It contains detailed information, building on and extending the work of Bhattacharjee et al. (2016), who analysed spatial heterogeneity and endogenous spatial dependence in Portugal. Regional house price records are linked with the coordinates of regions to track the spatial heterogeneity of house prices, and the region-related factors are employed in Beijing. Most of the previous empirical studies that combined geographic factors focused on the area of environment, health outcome, crimes and policy analyses (Hund et al., 2015; Neelon and Gelfand, 2014; Seliske et al., 2016; Terán-Hernández et al., 2016). These factors can be extended by our method with spatial partitioning, which can analyse the intensity of spill-over effects of explanatory factors.

5.1.3 Structure of This Chapter

The remainder of this chapter is organised as follows: Section 5.2 denotes the theory framework; Section 5.3 formulates the hypotheses that are tested in this chapter; Section 5.4 outlines the methodology and data; Section 5.5 analyses the empirical results; and Section 5.6 presents the concluding remarks.

5.2 Theoretical Framework

5.2.1 Theory of Residential Location

The residential location theory is emphasised as a field of economic study in terms of the growth of interest of economists (Evans, 1973). Prior to 1960s, the economic influences on residential location theory were rejected by socialists (Evans, 1973). It is unable to explain the investments in transportation to change the residential location in the field of sociology (Isard, 1956, p. 144). While Losch (1954) argues that the individual's choice of residential location is based on the maximum utility which in turn is based on the wages and the costs of good. The equilibrium pattern of town is considered with the short life of building and house conditions relived to building costs (Turvey, 1957). The residential location theory falls into intense debates between the field of economics and that of sociology during the 1950s.

Alonso (1964) demonstrates that the household location should be taken into economic factors based on the ‘concentric zone theory’ (Burgess, 1925) and ‘sector theory’ (Hoyt, 1939). Alonso (1964) argues that the increasing population and old residential property limits the implementation of ‘concentric zone theory’ in the real world referred to the ‘concentric zone theory’. The pattern of residential location is not completely explained by the filtering-down process in the ‘sector theory’. The assumptions made by sociologists (Burgess, 1925 and Hoyt, 1939), such as growing population, increasing stocks of the house, the relationship between house age and income of customers, are belonging to economic factors (Alonso, 1964). Richardson (1971) developed a trade-off theory, which ‘assumes household find its optimal location relative to the centre of the city by trading off travel costs’. This theory denotes that regarding the distance increases from the city centre, the rent of houses or the house costs would be declined. The household through maximising the utility of house location balances the costs of the house and satisfies more space for living. Richardson (1971) has a similar result with Alonso (1964) which provides the household location should be taken into economic factors. After the 1970s, the location theory is brought to the field of economics from uncertainty to the certainty.

Richardson (1971) describes a trade-off theory, which ‘assumes household find its optimal location relative to the centre of the city by trading off travel costs’. This theory denotes that through increasing the distance from city centre, the rent of houses or the house costs would be declined. The household through maximising the utility of house location balances the costs of the house and satisfies more space for living (Richardson, 1971).

Referred to the location analysis associating the components of spatial methods, a variety of investigations in housing development and housing investment could be entrenched. The housing developers, for example, design a prime case for the resource allocation approaches for housing location planning (Pace and Zhu, 2019). While several techniques in house location analysis are not based on resource allocation approaches but conceptual links between geography and valuation approaches. Related to the allocation of one or several facilities has valuable impacts on housing development or house price in space. For example, the analysis of delimitation of CBD is revealed referred to the representation of CBD is significant in urban development (Yu et al., 2015). The distance to CBD has impacts on house prices (Chen and Hao, 2008 and Huang et al., 2018). Fernandez et al., (2018) investigate open space value in an ideal setting for a natural experiment between Riverside County, with an open space conservation policy, and neighbouring San Bernardino County without the policy. Accordingly, the regions with alternative facilities or conditions (e.g., policy, household income, disease rates), which have geographical features, are valuable to investigate with locational analysis and spatial methods (e.g., crime analysis).

5.2.2 Concepts in Spatial Analysis

The term 'spatial effects' provides spatial dependence (spatial autocorrelation) and spatial heterogeneity. Spatial dependence describes the spatial relationship between variable values or locations. The spatial heterogeneity implicates that spatial distribution is instability or non-stationarity. Regarding a regression model, the spatial heterogeneity implies the non-constant error variances (heteroscedasticity) or the variable regression coefficients (Baltagi, 2013, pp. 319-320). When the model is specified inappropriately, the spatial heterogeneity will generate spatial autocorrelation in the residuals of the model (McMillan, 2003). As mentioned above, spatial dependence implies the scarcity of independence in terms of the observations of cross-sectional samples. For instance, house price's spatial dependence illustrates that the house price is relative to that of in the neighbouring locations due to there are other explainable variables except that of included in a regression model. Accordingly, the spatial effects occur due to the scarcity of the combination between the spatial distribution of the entities and the spatial partition of entities. The spatial effects could be due to the spillover effects (e.g., the influences of house price on that of neighbours) spatially correlated variables which have errors in measurement or omitted unobserved quantities. Anselin et al. (2008) suggest that the inherent spatial arrangement and structure delineate complicated patterns of interactions and dependencies. Therefore, both the spatial dependence and spatial heterogeneity are suggested to be contained in an appropriate spatial analysis.

Previous studies (Giussani and Hadjimatheou, 1991; Meen, 1999) explain that spatial dependence is the movement of house prices between one region and neighbouring regions. The increasing demand that occurs as a result of migration to regions where house prices are comparably low results in an increase in house prices. The spatial dependence is caused by information asymmetries suggested that new information referred to housing market in one area is transported gradually to other submarkets (Meen, 1999). Housing market provides attributes not only on spatial dependence but also on spatial heterogeneity. Wood (2003) provided that spatial heterogeneity is caused based on the speed of responses of national economic shocks in one region, where the housing market is more liquid and where new information affects house prices more rapidly than in the neighbouring regions. Meen (1999) argues that heterogeneity arises because of variations in household behaviours and household compositions. Pijnenburg (2017) suggested that the “disposition effect” (Shefrin and Statman, 1985) can explain the spatial heterogeneity. Disposition effect suggests that the sellers of delay selling their houses to avoid nominal losses. Thus, the speed of responses to national economic shocks is different in different regions across time so that there is spatial heterogeneity. In addition, the housing supply could be controlled by planning restrictions or by geographical features such as mountains or lakes. House prices, therefore, react differently to fluctuations in demand conditions if the supply cannot be adjusted. The present chapter, in contrast, does not rely on information about geographical constraints but instead applies some new projects and housing starts as the housing demand. The investigation also establishes models on the difference of house prices in the dynamics across space in order to analyse the spatial heterogeneity.

5.3 Literature Review and Hypotheses

A previous study (Kuethe and Pede, 2011) provided that the forecasts of house prices in the Western United States can be made more accurate by looking at house prices from neighbouring states. Meanwhile, they suggested that previous house prices can influence current house prices in the same space and time. Holly et al. (2011) also found that the dynamic spill-over affects house prices in the neighbouring areas. For China, Zhang et al. (2015) examine the house price spill-over effect with capital cities of Yangtze River Delta Economic Zone in China. Shanghai, Hangzhou, Nanjing, Hefei’s house prices index is tested over the period 2001-2014. They find the house price spill-overs in the Yangtze River Delta Economic Zone because of high market integration, but the direction and speed of spill-over are different. Chow et al. (2016) investigate house price convergence in 34 Chinese cities. They apply convergence model with contemporaneous spatial dependence in house prices and find that price convergence and positive spatial spill-over are both present. The spill-over narrows the gaps between the growth paths of house prices in neighbouring cities. The increasing demand that occurs as a result of migration to regions where house prices are comparably low results in an increase in house prices. Meen (1999) also illustrates that spatial dependence is caused by information asymmetries suggested that new information referred to the housing market in one area is transported gradually to other submarkets. Based on the ripple effect of spatial dependence on house prices and previous studies, this investigation has a hypothesis that:

H_1 The neighbouring regional house prices do not influence the local house prices.

Empirical evidence suggests spatial heterogeneity, such as planning constraints and geographical constraints, is different in different regions. Van Dijk et al. (2011) examined two groups of regions in the Netherlands and found that house prices within the same group had the same dynamics across time, while the dynamics were different across different groups. The spatial heterogeneity which exists is based on the different demand and supply of house price across clusters (Dieleman et al., 2000). For China, Zhang et al. (2015) examine the house price spill-over effect and the dynamic linkages among municipalities and capital cities of Yangtze River Delta Economic Zone in China between 2001-2014. The results provide that the movement of the population of Yangtze River Delta impacts in Hefei house price negatively, which means the regional house price leads to movement of population and the spillover effect of the house price. Chow et al. (2016) investigate house price convergence in 34 Chinese cities. They denote that population growth is the most influential factors that propel house prices regardless of the city of shock origin. Thus, this investigation has a hypothesis that:

H_2 The urban population influence house prices negatively.

The previous studies provide the determinates of house prices such as income (Liu and Xiong, 2018), housing supply (Fang et al., 2016), interest rate (Koss and Shi, 2018), unemployment rate (Drachal, 2016), urbanisation (Garriga et al., 2017) and local government tax (Shi and Lee, 2017). However, these studies did not address the spatial effects of the determinates of house prices. The literature analysing the spatial heterogeneity of house prices in terms of unemployment rate provides that the municipal unemployment rates denote significant positive spatial autocorrelation (Kondo, 2015). The movement of the population leads to the spillover effect of the house price which causes the spatial heterogeneity of house prices (Zhang et al., 2015). It is mentioned that local government tax is a significant factor to the house price when considering the spatial analysis of house price in China (Liu, 2013). Yu (2010) applied panel data econometrics to achieve the conclusion that the interest rate has a negative effect on house prices. Abate (2017) indicated a rising spatial correlation in house prices and income. While these studies ignore the regional partitioning spatial effects of the determinates of house prices. The influences of direct effects and indirect effects by partitioning technique which provides a significant impact on spatial econometrics (LeSage and Pace, 2010). It considers the influences of explanatory variables on different orders of neighbours. The partitioned direct effects clarify a picture of the spatial feedback effects (Elhorst, 2014). It is valuable to capture the determinates of house prices accounting for the measures within different geographical regions to the regulators of the housing market and city planners. Thus, this research regards the economic information as the driving force of house price spill-overs and has the following hypotheses:

H_3 Average wage of staff and workers of real estate do not have spill-over effects;

H_4 Income of residents does not have spill-over effects;

H_5 Taxes and other charges on principal business of enterprises for real estate development do not have spill-over effects;

H_6 Unemployment rate does not have spill-over effects;

H_7 Urban population does not have spill-over effects.

5.4 Methodology and Data

5.4.1 Spatial Matrix

In order to observe the spatial variation of house prices, in which the house price is influenced by house prices in neighbour regions, the spatial lag of the dependent variable should be estimated.[30] The spatial weight matrix depicts the relationship between an element and elements in surrounding regions. For instance, the spatial weight matrix, W_N, is provided for the region and the neighbouring regions. N represents the number of regions. W_N estimates an N×N matrix to determine the weight of neighbouring regions (Anselin et al., 2008). For instance, W_{ij} is an element in the weight matrix, W_N. i and j represent two different regions. Therefore, W_{ij} illustrates the number of neighbouring regions between the region i and region j. If there is a neighbouring region for the element W_{ij}, the value of W_{ij} is equal to 1. If there are no neighbouring regions between i and j, W_{ij} is equal to zero. According to the convention, W_{ii}, which is the diagonal element, is equal to zero. In this chapter, there are fifteen districts of Beijing. Thus, the investigation estimates a spatial weight matrix, W_{15}.

The calculation of weight element, W_{ij}, belongs to the dimension of the weighted matrix. The relevant dimension of the weight matrix defines the number of neighbours that influence the

[30] See Anselin, et al. (2008) for spatial variation in spatial panel econometrics, spatial variation interrupted that the house price in one region is influenced by neighbouring region house prices.

element in this weight matrix. Several methods can define the dimension of the weight matrix, such as inverse distance, fixed distance, K nearest neighbours and contiguity to set for neighbourhood effects. In a distance-based weight matrix, a threshold distance is specified such that all locations within the given distance are considered to be "neighbours". Alternatively, the k-nearest neighbour weight matrix is also based on distance, which is computed as the distance between a point and the number (k) of nearest neighbour points. Contrarily, the dimension of the weight matrix can be referred to tests. Global Moran's I test is an appropriate method for spatial correlation. If p-value of Global Moran's I is significant, there is a spatial lag or a spatial error in the model. Nevertheless, the dimension of the weight matrix should be defined first before Global Moran's I test. For instance, the previous study (Hoshino and Kuriyama, 2010) estimated the relative distance that regarded as a standard of the weight matrix in spatial error model (SEM). This investigation estimates a spatial weight matrix based on boundaries. There are two kinds of methods that select the appropriate spatial weights, namely rook contiguity and queen contiguity.

Figure 5.1 Rook Contiguity and Queen Contiguity

The differences between rook contiguity and queen contiguity illustrates whether the spatial element shares a boundary or not. Rook contiguity takes only four neighbours into account with common boundaries. Queen contiguity takes into account all eight surrounding cells, including common boundaries and common corners. For instance, if the element, W_{ij}, is denoted by shared boundary then it is called queen contiguity weights; otherwise, it is called rook contiguity weights (Figure 5.1). This chapter employs queen contiguity spatial weight for the model. Table 5.1 provides the spatial weight matrix for this investigation.

Table 5.1 Spatial Weight Matrix W_{15}

Region	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0
2	1	0	1	0	1	0	0	1	1	1	1	0	0	0	0
3	1	1	0	1	1	1	1	0	0	0	1	0	0	0	0
4	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0
5	1	1	1	1	0	1	0	0	0	1	0	0	0	0	0
6	0	0	1	1	1	0	1	0	0	1	0	0	0	0	0
7	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0
8	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0
9	0	1	0	0	0	0	0	1	0	1	0	1	1	1	0
10	0	1	0	0	1	1	0	0	1	0	0	0	1	0	1
11	0	1	1	0	0	0	1	1	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0
13	0	0	0	0	0	0	0	0	1	1	0	0	0	1	1
14	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0
15	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0

Additionally, the elements in the weight matrix are row standardised. After row standardised, the sum value of elements for each row is equal to one. The objective of row standardisation is to establish the proportional weights so that there are unequal numbers of neighbours. For instance, Table 5.2 provides the spatial weight matrix after row standardisation.

Table 5.2 Row Standardised Spatial Weight Matrix W_{15}

Region	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	1/3	1/3	0	1/3	0	0	0	0	0	0	0	0	0	0
2	1/7	0	1/7	0	1/7	0	0	1/7	1/7	1/7	1/7	0	0	0	0
3	1/7	1/7	0	1/7	1/7	1/7	1/7	0	0	0	1/7	0	0	0	0
4	0	0	1/3	0	1/3	1/3	0	0	0	0	0	0	0	0	0
5	1/6	1/6	1/6	1/6	0	1/6	0	0	0	1/6	0	0	0	0	0
6	0	0	1/5	1/5	1/5	0	1/5	0	0	1/5	0	0	0	0	0
7	0	0	1/3	0	0	1/3	0	0	0	0	1/3	0	0	0	0
8	0	1/3	0	0	0	0	0	0	1/3	0	1/3	0	0	0	0
9	0	1/6	0	0	0	0	0	1/6	0	1/6	0	1/6	1/6	1/6	0
10	0	1/6	0	0	1/6	1/6	0	0	1/6	0	0	0	1/6	0	1/6
11	0	1/4	1/4	0	0	0	1/4	1/4	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	1/2	0	0	0	0	1/2	0
13	0	0	0	0	0	0	0	0	1/4	1/4	0	0	0	1/4	1/4
14	0	0	0	0	0	0	0	0	1/3	0	0	1/3	1/3	0	0
15	0	0	0	0	0	0	0	0	0	1/2	0	0	1/2	0	0

In this investigation, panel data are employed. Thus, the model assumes that the spatial weight matrix does not change across time. The cross-sectional weight matrix, W_N, is stacked by T times. The equation is provided below:

$$W_{Nt} = I_T \otimes W_N \tag{5.1}$$

Thus, the spatial lagged dependent variable is represented as:

$$W_y = W_{NT}y = (I_T \otimes W_N)y \tag{5.1.1}$$

And the spatial lagged independent variables are represented as:

$$W_x = W_{NT}x = (I_T \otimes W_N)x \tag{5.1.2}$$

5.4.2 Spatial Autocorrelation Tests

Spatial autocorrelation tests assess the variable correlation which is relative to this variable's spatial location. This test approaches the variable features and the spatial attributes for the locations. Global Moran's I is one of the spatial autocorrelation tests. Global Moran's I tests the existence of the spatial autocorrelation for the model residuals. The value of Global Moran's I could be different between 1 and -1. If the value of Global Moran's I tends to 1, which is positively higher, the values in surrounding regions tend to be clustered. On the other hand, if the the value of Global Moran's I tends towards lower and negative, the values in surrounding regions tend to be interspersed. If the value of Global Moran's I is zero, the spatial autocorrelation does not exist in the model. This means that the samples are randomly distributed. In the sample, variable x has n observations at locations of i and j, the value of Global Moran's I equation is written as:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{W\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{5.2}$$

x_i = attribute value in area i;
n = number of areas.

$$W = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \tag{5.2.1}$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{5.2.2}$$

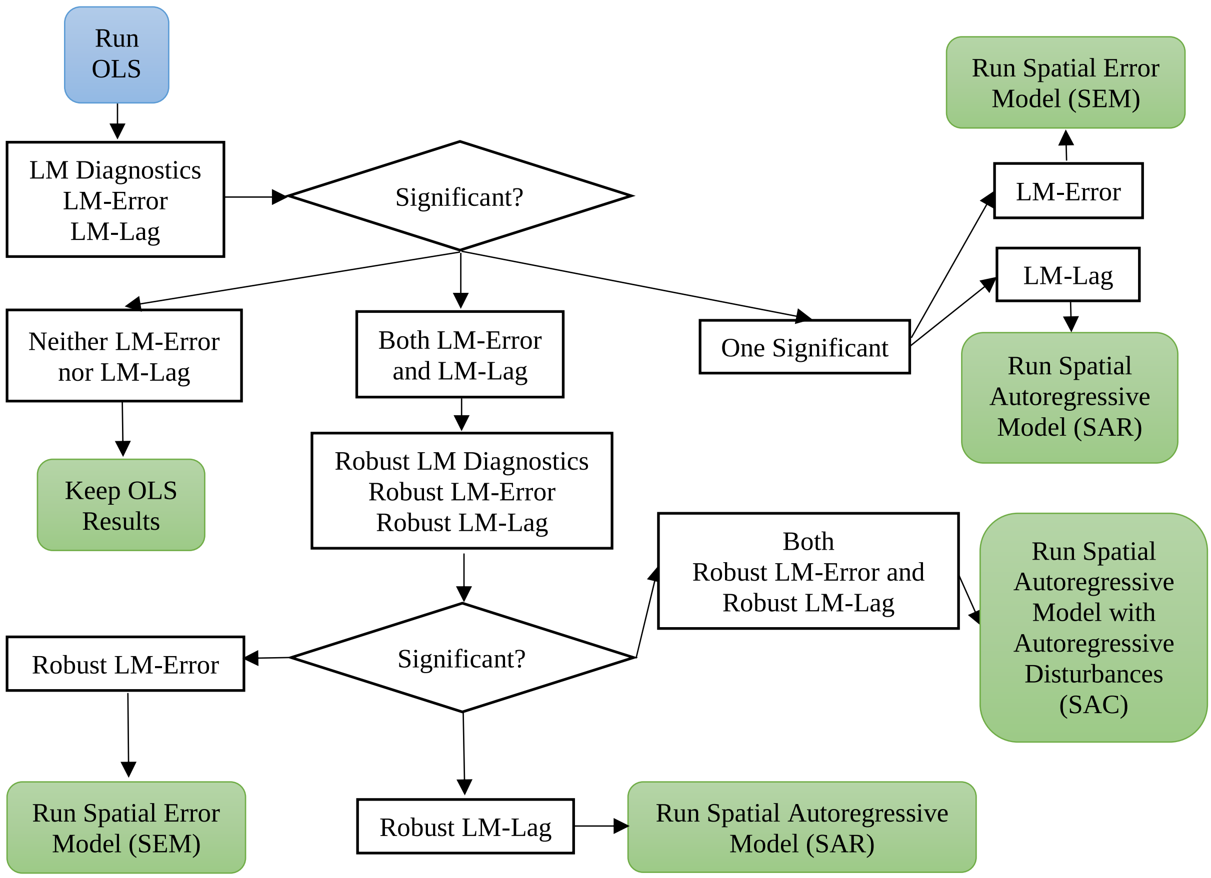
where x_i represents the attribute value in region i. n provides the number of observations for the whole regions. i and j represent the region i and region j. $\bar{x}$ is the mean value of variable x.

W_{ij} is an element in the spatial weight matrix, representing the spatial weight between region i and region j.

The Moran's I plot is a method to observe the distribution in Global Moran's I tests, which selects randomisation for more than 999 permutations. The Moran's I plot computes the distribution of Moran's I statistics under the null hypothesis by randomly re-allocating the observed values to the map. It repeats this process 999 times to yield the empirical histogram plot for the Moran's I statistics. The chart compares the reference distribution under the null hypothesis with the computed statistics and also indicates the values of the computed statistics, including the Moran's I value with its p-value based on the 999 permutations. The p-value would be the probability of obtaining the observed value of the Moran statistic, or one more extreme if the null hypothesis were accepted.

If the p-value of Global Moran's I is below 5%, and the coefficient of Global Moran's I is not zero, there is a spatial dependence in the model. In order to determine the type of spatial dependence, this investigation applies Lagrange Multiplier diagnostics (LM tests).

Figure 5.2 Process of Spatial Econometrics



The spatial dependence is divided into two types, which are spatial error and spatial lag. The spatial error indicates that the error terms of the model are correlated across different spatial elements. Spatial lag illustrates the dependent variable y in region i, and is influenced by the independent variable in both region i and region j. For instance, if the p-value of the LM-lag test is below 5%, the spatial lag model exists; if the p-value of the LM-error test is below 5%, the spatial error model exists. Thus, when there is a spatial error, and there is no spatial lag in the model, the investigation will apply spatial error model (SEM). When there is spatial lag and there is no spatial error, the investigation will employ spatial autoregressive model (SAR). When both LM-error and LM-lag are significant, the robust tests are employed to find a proper alternative. If the robust spatial error test and robust spatial lag test are both significant, the model will estimate a spatial autoregressive model with autoregressive disturbances (SAC).

5.4.3 Parametric Spatial Econometrics

In the spatial econometrics, the relevant variables are modelled with spatial weight matrix. In this approach, the surrounding region observations could be identified. There are several alternative models that could achieve the appropriate approach for the investigation. The spatial approaches include the spatial lag model (SAR), the spatial error model (SEM), and the joined approach accommodating of both spatial lag and spatial lag operations (SAC). These spatial econometric models establish assumptions for the formation spatial correlation in the sample. The general spatial autoregressive model with spatial autoregressive errors is given by:

$$P_{it} = \alpha + \tau P_{it-1} + \rho \sum_{j=1}^{N} W_{ij} P_{it} + \beta_k \sum_{k=1}^{k} X_{itk} + \nu_{it} \tag{5.3}$$

$$\nu_{it} = \lambda \sum_{j=1}^{N} W_{ij} \nu_{it} + \varepsilon_{it} \tag{5.3.1}$$

where P_{it} is a N×1 vector containing one observation of the dependent variable for each spatial element (i=1,…, N). N is the number of regions. t represents the observation at time t. P_{it-1} is the value of dependent variable for last year. ρ provides the parameters of spatial lag. λ illustrates the parameters of spatial error. X_{it} represents the vector of independent variables, which are explanatory variables as well. The vector X_{it} consists of a N×K matrix. K is the number of explanatory variables. β provides the coefficient of K explanatory variable. The parameters λ and ρ are with respect to the spatial autocorrelation coefficients. In most cases of house prices analyses, the spatial autocorrelation coefficients are positive so that cluster the value of residential house prices.[31] In the spatial error model (SEM), ρ is equal to zero and λ is unequal to zero. The error terms, υ_{it}, are independent and identically distributed. In the spatial autoregressive model (SAR), λ is equal to zero and ρ is unequal to zero. Spatial lag term is endogenous and refers to the result of the two-directionality of neighbouring relations in space. Thus, the appropriate method is to employ maximum likelihood estimator or GMM estimator in SAR. Nevertheless, in the spatial autoregressive model with autoregressive disturbances (SAC), λ and ρ are both unequal to zero. Spatial Durbin model (SDM) is a generalisation of the SAR model which also includes spatially weighted independent variables as explanatory variables, and is written as:

$$P_{it} = \alpha + \tau P_{it-1} + \rho \sum_{j=1}^{N} W_{ij} P_{it} + \beta_k \sum_{k=1}^{k} X_{itk} + \theta_k \sum_{k=1}^{k} \sum_{j=1}^{N} W_{ij} X_{itk} + \varepsilon_{it} \qquad (5.4)$$

Table 5.3 Summary of Spatial Model Assumptions

Assumptions	Neighbouring Regions Effects	Unspecified Characteristics Effects of Neighbouring Regions	Explanatory Effects from Neighbouring Regions
	(ρ≠0)	(λ≠0)	(θ≠0)
Spatial Autoregressive Model (SAR)	√		
Spatial Error Model (SEM)		√	
Spatial Autoregressive Model with Autoregressive Disturbances (SAC)	√	√	
Spatial Durbin Model (SDM)	√		√

Table 5.3 illustrates the summary of spatial models and the assumptions of neighbouring regions for the different models. In the investigation, if the autocorrelation in the error term is inconsiderate, the incorrect standard errors will affect the efficiency of the model. Veie and Panduro (2015) provided that the disregard of positive correlation in the error terms results in overestimating significance levels. For instance, the value of parameters for spatial lagged terms, such as ρ and λ, will be increased when the spatial correlation originates from the spatial error terms correlated with the independent variables. In terms of the correlation of spatial errors, the spatial model contributes the unknown spatial characteristics. Accordingly, spatial error model (SEM) is an appropriate approach for the real estate market analyses (Veie and Panduro, 2015). McMillen (2012) illustrated that the method of the spatial error model (SEM) is similar to random effects in panel data estimation or feasible generalised

[31] See Veie & Panduro (2015) for an alternative to the standard spatial econometric approaches in hedonic house price models.

least squares (FGLS). McMillen (2012) also emphasises that the spatial error model structures a spatial parameter (λ) that could be influenced by the dimension of spatial weight matrix.

The spatial lag model (SAR) illustrates the direct spill-over effects, showing that one factor in its location is affected by the surrounding regions factor. In the housing market, the spatial lag model assumes that house prices are influenced by those of neighbouring regions. Le-Sage and Pace (2009) state that spill-overs effects depict how house prices in less expensive regions are increased by higher prices in neighbouring regions. The wealthier households move in the regions, and consequently adjust the distribution of neighbourhood, increasing house price. Alternatively, the spill-over effects are derived from information asymmetries.[32] Meen (1999) described that house sellers and buyers prefer to set an appropriate house price obtaining the prices of houses with similar characteristics in neighbouring location. Information about previous transactions will likewise inform assumptions about the future house prices in this region. Pijnenburg (2017) indicates that the increasing demand for house in one region when prices in a neighbouring region are comparably lower will cause spill-over effects. In most applications of the spatial lag model, that distinction is not made. As a thought experiment, consider the expansion of the central business district (CBD) area. An increase in access to the CBD will raise the price of not just one home but also the neighbouring properties. The prices of surrounding properties are themselves outcome variables and as such are affected by changes in the attractiveness of the location.

Gibbons and Overman (2012) emphasises that it is also essential to consider the theoretical background to establish a model referred to statistical tests. Spatial regression models explore the complicated spatial dependence structure in the spatial elements. In the spatial structure, the explanatory factors influence the dependent variable in its location is direct spill-overs effects. The explanatory factors likewise affect the surrounding regions value indirectly (indirect spill-overs effects).[33] According to the spatial models, the spatial lag model (SAR) provides the presence of direct effects, indirect effects and total marginal effects. LeSage and Pace (2009) provide that the distinctions between these effects rely on the degree of influence from one region and the degree of influence from the neighbouring regions. For instance, the direct effect illustrates that the explanatory variable in region i influences the dependent variable in region i at the same time. The indirect effect explores how the effect on the

[32] See Meen (1999) for spatial aggregation, spatial dependence and predictability in the UK house market.
[33] See Le-Sage & Pace (2009) for introduction to spatial econometrics.

dependent variable in region i is associated with a change in an explanatory variable in other regions. A similar interpretation is given by Won, Phipps and Anselin et al. (2003). The equation of marginal prices for a house (total effects) is written as:

$$(I - \rho W)P_t = \alpha + \tau P_{it-1} + \beta_k \sum_{k=1}^{k} X_{itk} + \theta_k \sum_{k=1}^{k} \sum_{j=1}^{N} W_{ij} X_{itk} + \varepsilon_{it} \quad (3.5)$$

where I and $(I - \rho W)$ are matrices. The change of P as regards X (i.e. $\partial \mathrm{P}/\partial \mathrm{X}$) results in spatial direct effects and indirect (spill-over) effects (Autant-Bernard and LeSage, 2011). Elhorst (2014) summarises the parameters of direct effect and indirect effect in the alternative spatial models:

Table 5.4 The Parameters of Direct Effects and Indirect Effects in Spatial Models

	Direct Effect	Indirect Effect (spill-overs effects)
OLS/SEM	βk	0
SAR/SAC	Diagonal entries of $(I - \rho W)^{-1}\beta_k$	Off-diagonal entries of $(I - \rho W)^{-1}\beta_k$
SDM	Diagonal entries of $(I - \rho W)^{-1}(\beta_k + W\theta_k)$	Off-diagonal entries of $(I - \rho W)^{-1}(\beta_k + W\theta_k)$

The direct effects and indirect effects provide the influences of a factor from one region and the first order region (Figure 5.3). Figure 5.3 provides the order of neighbouring regions. First order neighbours are those which lie immediately next to the regions being observed. However, the direct effects and indirect effects do not illustrate the influences of more distant neighbours, such as third order neighbouring regions. According to Jensen and Lacombe (2012), the degrees of influence of an explanatory variable on a dependent variable differ widely, depending on location. To deal with this, LeSage and Pace (2010) segmented the influences of direct effects and indirect effects to explore the influences of neighbours from different areas. Jensen and Lacombe (2012) developed this partitioning equation in terms of the spatial model, which is written as:

$$\frac{\partial Y_{it}}{\partial X_{kt}} = \left(I - \rho W_{Y_{it}}\right)^{-1} (\beta_k + W\theta_k) \quad (3.6)$$

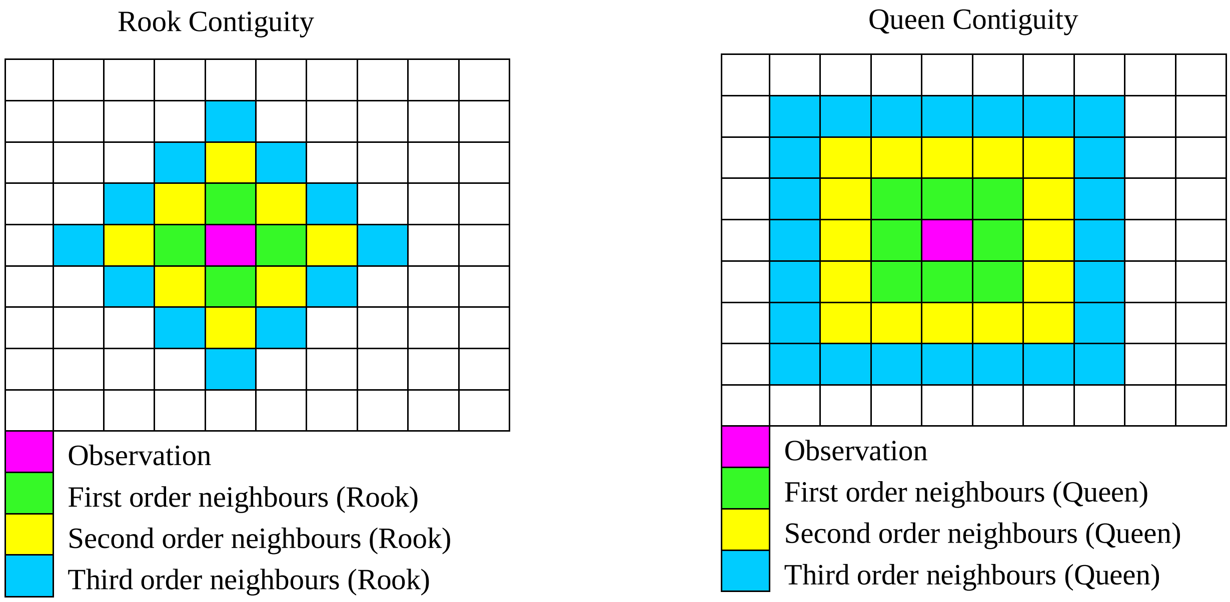
where

$$\left(I - \rho W_{Y_{it}}\right)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots + \rho^N W^N \quad (3.6.1)$$

The impacts are relative to each order neighbourhood can be illustrated as:

$$\begin{aligned} &\left(I - \rho W_{Y_{it}}\right)^{-1} (\beta_k + W\theta_k) \\ &= \underbrace{(I\beta_k + W\theta_k)}_{\mathrm{W}^{(1)}} + \underbrace{(\rho W\beta_k + \rho W^2\theta_k)}_{\mathrm{W}^{(2)}} + \underbrace{(\rho^2 W^2\beta_k + \rho^2 W^3\theta_k)}_{\mathrm{W}^{(3)}} + \cdots \end{aligned} \quad (3.6.2)$$

Figure 5.3 Order of Neighbourhood



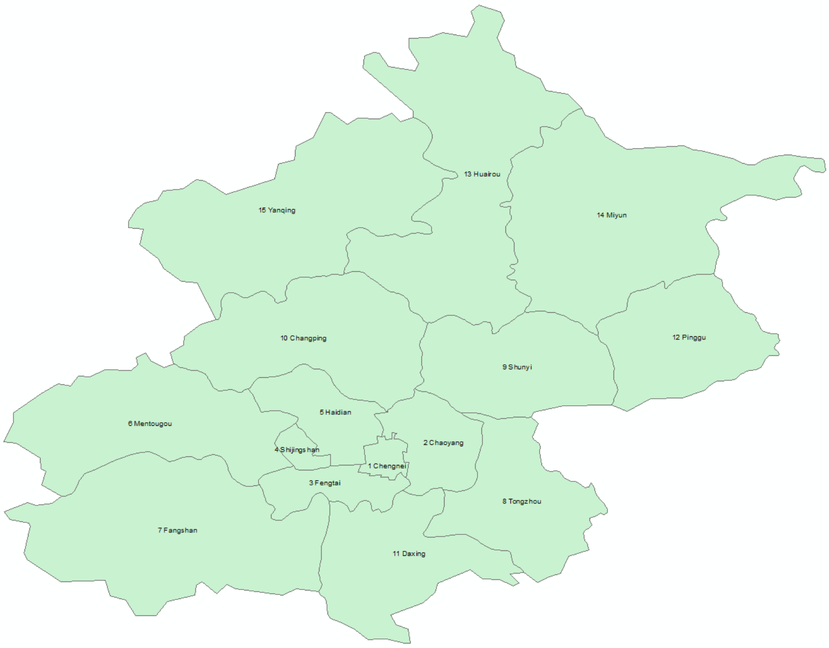
$W^{(i)}$ represents the spatial weight matrix of i^{th} order neighbours. Regarding to the order of neighbourhood, the lower order $W^{(i)}$ illustrates the closed neighbours, such as first-order neighbours $W^{(1)}$ (Figure 5.3). The higher order $W^{(i)}$ indicates the distant neighbours, such as first-order neighbours $W^{(3)}$. The partitioning technique provides a significant implication for spatial econometrics. It considers the influences of explanatory variables on different orders of neighbours. In this chapter, the partitioning technique is employed to analyse the influences of economic fundamentals on house prices. In contrast, previous studies apply this method to explore the influences of geographic features on property prices.[34]

5.4.4 Study Area and Data

This research addresses the area of Beijing that lies within the real estate development in Beijing. The government demarcates the core area of Beijing by Dongcheng district, Xicheng district, Xuanwu district, Chongwen district, Haidian district, Chaoyang district and Fengtai district. The surrounding districts of Beijing are Shijingshan, Changping, Tongzhou, Daxing, Shunyi, Huairou, Fangshan, Mentougou, Pinggu, Miyun and Yanqing. In total, there are 18 districts in Beijing. Due to the limited data, this investigation combines the districts of Dongcheng, Xicheng, Xuanwu and Chongwen into one region, which is called "Chengnei", for analysis. Figure 5.4 provides the map of fifteen districts in Beijing.

[34] See Hui & Liang (2016) for spatial spill-over effect of urban landscape views on property price.

Figure 5.4 Map of Fifteen Districts in Beijing



In the empirical analysis, this chapter employs samples of regional house price records containing a total of 675 observations. The sample period spans 2003 – 2013 annually. The data are retrieved from the official website of the National Bureau of Statistics of China and the World Bank database. The research investigates the determinants of house prices in fifteen districts of Beijing. The regional house price records include the longitude and latitude of the centre of regions respectively in order to calculate the distance between region and airport and the distance between region and CBD.

Table 5.5 Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Log House Price	165	3.95	0.38	3.04	4.78
Log Number of New Projects	165	3.07	0.21	2.77	3.56
Log Size of Building Started	165	3.28	0.08	3.14	3.41
Log Average Wage	165	4.71	0.18	4.40	4.97
Log Income	165	4.02	0.19	3.70	4.30
Log Tax	165	2.23	0.28	1.72	2.60
Log Urban Population	165	1.67	0.04	1.60	1.73
Unemployment Rate	165	0.042	0.001	0.04	0.043
Central Bank Interest Rate	165	0.064	0.005	0.058	0.073
Distance to Beijing Capital Airport (km)	165	35,759	15,025	6,912	67,652
Distance to CBD (km)	165	33,303	19,788	6,303	74,130

In order to provide an overview of the sample, Table 5.5 summarises the number of observations for each variable. Mean of the sample, standard deviation of the sample, minimum of the sample and maximum of the sample are provided to estimate this descriptive statistic. House Price is the dependent variable and the other variables are independent variables. All of the variables are the average value for each district in Beijing.

5.5 Empirical Findings

5.5.1 Spatial Dependence and Spatial Heterogeneity

The results of the examination of the determinants in the property sector are presented in the panel data regression models and are analysed using different estimators tested. In both the non-spatial regression and spatial econometrics regression, the investigation contains the house price of the previous year, which is the lag (1) house price, in terms of the dynamic estimation.

Table 5.6 and Table 5.7 test the influences of the number of new projects, size of building starts and the average wage of staff and workers in the real estate market on house prices with static models and dynamic models, respectively (Model 1). The investigation tests each estimator with OLS, fixed effects and random effects for the house prices in the combined 15 regions. It is found that the p-value of the Hausman Test can accept the null hypothesis and that random effect is appropriate for Model 1. Based on the result of SAC (Table 5.6), the average wage of employees in the real estate market leads to an increase in house price by 1.367% significantly. This finding is in line with 'the sector theory' (Hoyt, 1939), because the differences in household income cause the changes of residential location and house prices. Thus, this result support Hui and Gu (2009) who conclude that income is a significant factor affecting house price levels in Beijing Area. The number of new projects influence the house price positively but not significantly. This result is not in line with Zhang et al. (2015). The results also found that the distance from district to CBD influenced the house price significantly and negatively; which means the closer the house location is to CBD, the higher the price of a house will be. This finding is in line with the theory of 'the concentric zone' (Burgess, 1925), which explains that the development of ideal construction of the city expands from its CBD. The workers live near CBD aims to easy access to their work. Thus, the demand for house surrounding CBD is high, which causes the increase in house price. The distance from district to CBD influenced the house price significantly and negatively.

Moreover, the investigation found size of building starts, which instead of the supply of houses, influences house prices positively by 0.336%, but not significantly in SAC model. This result is in line with Hanink et al. (2012) and Zhang et al. (2018) who provide house starts is a potential determination of new construction rate which reflects the supply of housing market in Beijing. This finding is similar to the theory of 'the supply of space' (Evans, 1973), which provides that there is an equilibrium relationship between the density and revenue of houses in the theory of the supply of space. Even though there is enough space for construction, the irrational density of buildings leads to lower revenues of the house. Thus, the uncertainties of the model are more appropriate to explain the results in SEM model, which presents size of building starts, which instead of the supply of houses, influences house prices positively by 0.388%. However, the result is not very significant. Thus, the result is similar to Evans (1973), who suggests a rational space and density of constructions are significant to households. Across the data over the time, these results are similar to the previous study (Pijnenburg, 2017). Though the previous studies analysed data from different countries, the results correspond to economic theory.

For the test of heteroskedasticity in the OLS, fixed effects and random effects, Breusch-Pagan test is applied. The results show the p-value below 0.05, which strongly rejects the null hypothesis. This means there is heteroskedasticity in the random estimator and that random estimator is inefficient. The Breusch-Godfrey LM test provides there is serial autocorrelation in the panel model, in which the p-value is 0 and that random estimator is inefficient. Through the Global Moran's I test, the LM-error test and the LM-lag test, the results provide that there is spatial autocorrelation on both spatial error and spatial lag. In terms of Akaike Information Criterion (AIC), it is sufficient evidence for the efficient model when AIC is smaller. The spatial error model (SEM) is a compatible model in the spatial analysis. In the SEM model (Table 5.6), the results provide that the coefficient of the average wage increases to 1.66% and the coefficient of the average wage increases to 0.39%. Spatial error model (SEM) focuses on the influences of neighbouring unobserved characteristics on house prices. According to the null hypothesis of SEM, ρ equals to zero so that the neighbouring house prices of the previous year are removed. The SEM model estimates the parameters λ, which are the autocorrelation coefficients of neighbouring unobserved characteristics on the house prices of the previous year. The result provides that the spatial autocorrelation coefficient of λ is 0.0074. This means the house prices are influenced by the neighbouring unobserved characteristics significantly and positively.

When adding the lag (1) house prices variable, this investigation establishes dynamic models for testing the spatial heterogeneity for Model 1 (Table 5.7). Through the Global Moran's I test, the LM-error test and the LM-lag test, the results provide that there is spatial autocorrelation on spatial error. In terms of AIC, SEM is an efficient model. It is found that the house prices of the previous year influenced the house price by 0.887% positively and significantly. This means house prices in neighbouring regions spill-over more in times of increasing neighbouring house prices. Thus, the hypothesis H1 is rejected. This finding is in line with an earlier study (Pijnenburg, 2017). This result is also similar to Zhang et al. (2015) and Chow et al. (2016), who find that the house price is influenced by that of neighbouring regions. Thus, this study confirms house price is influenced by that of neighbouring regions in Beijing area, which means Beijing house price has a spatial dependence. The Wooldridge LM Test suggests there is no more spatial autocorrelation in the data, according to the p-value of 0.37 which is above 0.05. The Breusch-Pagan Test indicates remaining heteroskedasticity in the residuals. In conclusion, the unobserved characteristics of the neighbouring regions influence house price significantly in the long term and short term, which is a dynamic analysis. The short-term effects of unobserved characteristics in the neighbouring regions are more than long-term unobserved characteristics in the neighbouring regions.

Table 5.6 Test Results for Panel Model and Spatial Models

Panel:

$$logP_{it} = \alpha_0 + a_1 logNP_{it} + a_2 logBS_{it} + a_3 logAW_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$$

Spatial:

$$logP_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logNP_{it} + a_2 logBS_{it} + a_3 logAW_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$$

	Random	SAC	SAR	SEM	SDM
Num of New Projects	0.0105 (0.18)	0.0127 (0.14)	0.0102 (0.13)	0.0145 (0.18)	0.0270 (0.13)
Size of Building Started	0.353** (2.34)	0.313 (1.40)	0.336 (1.62)	0.388* (1.95)	0.248 (0.79)
Average Wage	1.649*** (23.51)	1.367*** (11.85)	1.565*** (15.94)	1.663*** (17.82)	1.309*** (6.42)
Distance to Beijing Capital Airport (km)	2.38E-07 (0.05)	1.22E-07 (0.88)	1.64E-07 (1.22)	1.57E-07 (1.15)	1.28E-07 (-0.35)
Distance to CBD (km)	-6.79E-06** (-2.05)	-5.30E-06*** (-4.79)	-5.31E-06*** (-5.06)	-5.81E-06*** (-5.64)	-2.64E-06 (-0.83)
Rho(ρ)	-	0.039*** (3.82)	0.012*** (4.18)	-	0.0784*** (3.54)
Lambda(λ)	-	0.0284** (2.44)	-	0.00742*** (-2.96)	-
Sigma(σ)	-	0.194*** (18.14)	0.200*** (18.17)	0.203*** (18.17)	0.191*** (17.91)
Constants	-4.788*** (-6.70)	-3.689*** (-3.66)	-4.633*** (-4.81)	-5.186*** (-5.62)	-3.143*** (-3.03)
Adjusted r2	0.654	0.183	0.338	0.531	0.047
VIF	1.35	-	-	-	-
Hausman p-value	0.21 1	-	-	-	-
Breusch-Godfrey LM p-value	83.02 0	-	-	-	-
Breusch-Pagan p-value	104.5 0	-	-	-	-
Global Moran's I p-value	0.173 0	-	-	-	-
LM-Error Test p-value	10.6 0	-	-	-	-
Robust LM-Error Test p-value	8.06 0.01	-	-	-	-
LM-Lag Test p-value	15.9 0	-	-	-	-
Robust LM-Lag Test p-value	13.3 0	-	-	-	-
AIC	-	0.127	0.091	0.064	2.425
Wooldridge LM p-value	-	0.587 0.443	0.587 0.443	0.587 0.443	0.773 0.379
Breusch-Pagan p-value	-	92 0	81.02 0	70.11 0	152.3 0

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

Breusch–Pagan test is used to test for heteroskedasticity in the model;

Breusch-Godfrey LM test is used to test for serial correlation;

Moran's I tests for the presence of spatial autocorrelation of residuals, the value is between 1 and −1; positive Moran's I means values in neighbouring positions tend to cluster; negative Moran's I means values are interspersed; zero of Moran's I, there is no spatial autocorrelation, means the data are randomly distributed.

Spatial error: the error terms across different spatial units are correlated.

Spatial lag: the dependent variable y in place i is affected by the independent variables in both place i and j.

Lagrange Multiplier Diagnostics (LM): LM-Error Test and LM-Lag Test determines the type of spatial dependence - spatial error or spatial lag (Robust tests used to find a proper alternative, only use robust forms when BOTH LMerror and LMlag are significant). If p-value of LM less than 0.05 indicates there are spatial autocorrelation on error or lag.

Table 5.7 Test Results for Dynamic Panel Model and Dynamic Spatial Models

Panel:

$$logP_{it} = \alpha_0 + \tau logP_{it-1} + a_1 logNP_{it} + a_2 logBS_{it} + a_3 logAW_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$$

Spatial:

$$logP_{it} = \alpha + \tau P_{it-1} + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logNP_{it} + a_2 logBS_{it} + a_3 logAW_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$$

	Random	SEM	SDM
Lag(1) House Price	0.897*** (21.84)	0.887*** (23.86)	0.88*** (23.37)
Num of New Projects	0.0882** (2.02)	0.0897** (2.05)	0.168* (1.70)
Size of Building Started	0.234** (-2.05)	0.268*** (-4.94)	0.121 (-0.66)
Average Wage	0.0685 (0.77)	0.07 (1.07)	0.003 (0.02)
Distance to Beijing Capital Airport (km)	1.07E-07 (0.15)	5.52E-07 (0.77)	1.48E-07 (-0.09)
Distance to CBD (km)	-1.46E-06** (-2.50)	-1.16E-06** (-1.99)	-9.20E-07 (-0.61)
Rho(ρ)	-	-	0.112*** (6.86)
Lambda(λ)	-	0.0154** (2.44)	-
Sigma(σ)	-	0.103*** (18.16)	0.091*** (17.76)
Constants	0.703 (1.23)	0.77 (0.75)	0.44 (0.64)
Adjusted r2	0.914	0.899	0.731
VIF	2.18	-	-
Hausman p-value	4.73 0.32	-	-
Breusch-Godfrey LM p-value	10.9 0	-	-
Breusch-Pagan p-value	22.7 0	-	-
Global Moran's I p-value	2.35 0.02	-	-
LM-Error Test p-value	48.9 0	-	-
LM-Lag Test p-value	1.07 0.3	-	-
AIC	-	0.014	4.96
Wooldridge LM p-value	-	9.05 0.37	5.98 0.14
Breusch-Pagan p-value	-	16.7 0	159.4 0

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

Breusch–Pagan test is used to test for heteroskedasticity in the model;

Breusch-Godfrey LM test is used to test for serial correlation;

Moran's I tests for the presence of spatial autocorrelation of residuals, the value is between 1 and −1; positive Moran's I means values in neighbouring positions tend to cluster; negative Moran's I means values are interspersed; zero of Moran's I, there is no spatial autocorrelation, means the data are randomly distributed.

Spatial error: the error terms across different spatial units are correlated.

Spatial lag: the dependent variable y in place i is affected by the independent variables in both place i and j.

Lagrange Multiplier Diagnostics (LM): LM-Error Test and LM-Lag Test determines the type of spatial dependence - spatial error or spatial lag (Robust tests used to find a proper alternative, only use robust forms when BOTH LMerror and LMlag are significant). If p-value of LM less than 0.05 indicates there are spatial autocorrelation on error or lag.

Table 5.8 and Table 5.9 test the influences of income, unemployment rates and central bank interest rates on house prices (Model 2). From the Hausman Test, the results show that random effect is appropriate for this model based on p-value is 1. The Breusch-Pagan Test shows the p-value is below 0.05, which means there is heteroskedasticity in the random estimator and that the random estimator is inefficient. The Breusch-Godfrey LM test provides that there is serial autocorrelation in the panel model, where the p-value is 0 and the random estimator is inefficient.

Through the Global Moran's I test, the LM-error test and the LM-lag test, it is found there is spatial autocorrelation on spatial lag. The spatial lag model (SAR) is a compatible model in the spatial analysis. In the SAR model (Table 5.8), the results provide that income leads to the increase in house price by 1.59% significantly. This result is also line with Shen and Liu (2004). The income significantly influences the house price in Beijing. This finding is in in line with the theory of 'the concentric zone' (Burgess, 1925), which presents the high-income group 'who have escaped from the area of deterioration' changes the demand of residential location. Thus, house price would increase. This is similar the empirical results of this investigation that income leads to the increase in house price. The unemployment rate influences the house price negatively but not significantly. This result is not in line with Harris et al. (2013). This means the unemployment rate does not influence the house price in Beijing. Central bank interest rates influence house prices negatively and significantly by 12%. This result is similar to the prior study (Li and Chand, 2013). This means the interest rate influence urban house prices negatively in Beijing area. The investigation also found that the distance from district to CBD influenced the house price significantly and negatively; which means the closer the house location is to CBD, the higher the price of a house will be. This finding is also in line with 'the concentric zone' (Burgess, 1925). Spatial autoregressive model (SAR) is focused on the influences of neighbouring dependent variable. According to the null hypothesis of SAR, λ equals to zero so that the neighbouring unobserved characteristics of the dependent variables are removed. The SAR model provides estimates of the parameters ρ, which is the spatial autocorrelation coefficient of neighbouring dependent variable. In Table 5.8, the result provides the spatial autocorrelation coefficients of ρ is 0.01 in SAR. These means the house price is influenced by the neighbouring house price by 0.1%

Table 5.8 Test Results for Panel Model and Spatial Models

Panel: $logP_{it} = \alpha_0 + a_1 logGDP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logGDP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$			
	Random	SAR	SDM
GDP	1.672*** (25.08)	1.59*** (16.26)	1.386*** (6.09)
Unemployment Rate	-0.051 (-0.30)	-0.047 (-0.19)	0.058 (0.20)
Central Bank Interest Rate	-12.64*** (-3.97)	-12.02*** (-2.63)	-11.38 (-1.16)
Distance to Beijing Capital Airport (km)	2.38E-07 (0.05)	1.59E-06 (1.23)	1.08E-06 (-0.30)
Distance to CBD (km)	-6.79E-06** (-2.05)	-5.36E-06*** (-5.28)	-2.79E-06 (-0.89)
Rho(ρ)	-	0.0111*** (4.18)	0.0588** (2.24)
Sigma(σ)	-	0.193*** (18.17)	0.188*** (17.99)
Constants	-1.539 (-1.62)	-1.551 (-1.15)	-1.169 (-0.88)
Adjusted r2	0.715	0.705	0.923
VIF	1.79	-	-
Hausman p-value	0.2 1	-	-
Breusch-Godfrey LM p-value	112.8 0	-	-
Breusch-Pagan p-value	90.6 0	-	-
Global Moran's I p-value	0.112 0.02	-	-
LM-Error Test p-value	4.42 0.04	-	-
Robust LM-Error Test p-value	2.86 0.09	-	-
LM-Lag Test p-value	15.9 0	-	-
Robust LM-Lag Test p-value	14.3 0	-	-
AIC	-	0.085	1.38
Wooldridge LM p-value	-	3.02 0.08	6.08 0.01
Breusch-Pagan p-value	-	92.14 0	149.2 0
** p<0.10 ** p<0.05 *** p<0.01*			
T-statistic are in parenthesis			
Breusch–Pagan test is used to test for heteroskedasticity in the model;			
Breusch-Godfrey LM test is used to test for serial correlation;			
Moran's I tests for the presence of spatial autocorrelation of residuals, the value is between 1 and −1; positive Moran's I means values in neighbouring positions tend to cluster; negative Moran's I means values are interspersed; zero of Moran's I, there is no spatial autocorrelation, means the data are randomly distributed.			
Spatial error: the error terms across different spatial units are correlated.			
Spatial lag: the dependent variable y in place i is affected by the independent variables in both place i and j.			
Lagrange Multiplier Diagnostics (LM): LM-Error Test and LM-Lag Test determines the type of spatial dependence - spatial error or spatial lag (Robust tests used to find a proper alternative, only use robust forms when BOTH LMerror and LMlag are significant). If p-value of LM less than 0.05 indicates there are spatial autocorrelation on error or lag.			

Table 5.9 Test Results for Dynamic Panel Model and Dynamic Spatial Models

Panel:

$$logP_{it} = \alpha_0 + \tau logP_{it-1} + a_1 logGDP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$$

Spatial:

$$logP_{it} = \alpha + \tau logP_{it-1} + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logGDP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$$

	Fixed	SEM	SDM
Lag(1) House Price	0.844*** (21.36)	0.864*** (23.06)	0.865*** (22.98)
GDP	0.331*** (4.06)	0.243*** (2.71)	0.189 (1.53)
Unemployment Rate	-0.155 (1.17)	-0.0194 (0.37)	-0.186 (1.34)
Central Bank Interest Rate	-5.423** (-2.16)	-6.902** (-2.31)	-4.596 (-0.96)
Distance to Beijing Capital Airport (km)	1.14E-07 (0.17)	1.94E-07 (0.25)	1.75E-07 (0.10)
Distance to CBD (km)	-1.78E-06*** (-3.11)	-1.42E-06** (-2.09)	-1.23E-06 (-0.81)
Rho(ρ)	-	-	0.0979*** (5.28)
Lambda(λ)	-	0.108*** (6.48)	-
Sigma(σ)	-	0.091*** (17.78)	0.091*** (17.83)
Constants	-0.885 (-1.20)	0.0198 (0.66)	-0.618 (-0.95)
Adjusted r2	0.917	0.913	0.793
VIF	2.46	-	-
Hausman p-value	16.14 0	-	-
Breusch-Godfrey LM p-value	7.7 0.01	-	-
Breusch-Pagan p-value	27.4 0	-	-
Global Moran's I p-value	2.23 0.03	-	-
LM-Error Test p-value	41.75 0	-	-
LM-Lag Test p-value	1.59 0.207	-	-
AIC	-	0.012	3.81
Wooldridge LM p-value	-	13.2 0	8.16 0
Breusch-Pagan p-value	-	27 0	159 0

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

Breusch–Pagan test is used to test for heteroskedasticity in the model;

Breusch-Godfrey LM test is used to test for serial correlation;

Moran's I tests for the presence of spatial autocorrelation of residuals, the value is between 1 and −1; positive Moran's I means values in neighbouring positions tend to cluster; negative Moran's I means values are interspersed; zero of Moran's I, there is no spatial autocorrelation, means the data are randomly distributed.

Spatial error: the error terms across different spatial units are correlated.

Spatial lag: the dependent variable y in place i is affected by the independent variables in both place i and j.

Lagrange Multiplier Diagnostics (LM): LM-Error Test and LM-Lag Test determines the type of spatial dependence - spatial error or spatial lag (Robust tests used to find a proper alternative, only use robust forms when BOTH LMerror and LMlag are significant). If p-value of LM less than 0.05 indicates there are spatial autocorrelation on error or lag.

significantly and positively. Thus, the hypothesis H1 is rejected. This result is similar to Zhang et al. (2015) and Chow et al. (2016), which means Beijing house price has a spatial heterogeneity. In respect to adding the lag (1) house prices variable, it is found that spatial autocorrelation of spatial lag house prices is not significant.

However, the house prices of the previous year influence the house price by 0.86% positively and significantly. This means house prices in neighbouring regions spill-over more in times of increasing neighbouring house prices. The Breusch-Pagan Test indicates remaining heteroskedasticity in the residuals.

Table 5.10 and Table 5.11 test the influences of 'taxes and other charges on principal business of enterprises for real estate development' (Tax) on the house prices (Model 3). The Hausman Test accepts the null hypothesis that random effect is appropriate for this model. Based on the result of SAR model (Table 5.10), taxes and other charges on principal business of enterprises for real estate development lead to the increase in house price by 1.07% significantly. This result is similar to the previous studies (Li and Chand, 2013; Liu, 2013; Shi and Lee, 2017), which means the taxes and other charges on principal business of enterprises for real estate development influence house prices negatively and significantly in Beijing. This finding is in line with 'trade-off theory of residential location' (Evans, 1973), which provides the maximum utility of household is the objective of the choice of location. The increasing tax added the costs of construction, and then the developers will increase the house selling price so that balance the costs. When the household considers the house price, they will change the location of living so that the patterns of residential location changes. Thus, the tax could influence the house price, which is appropriate for trade-off theory. The distance from district to CBD influences house prices significantly and negatively; which means the closer the house location is to CBD, the higher the price of a house will be. This finding is similar with 'the concentric zone' (Burgess, 1925). Across the data over the time, these results are similar to the previous study (Pijnenburg, 2017). Though the previous studies analysed the different countries, the results correspond to economic theory. For the test of heteroskedasticity in random effects, the Breusch-Pagan test shows the p-value below 0.05, which strongly rejects the null hypothesis. This means there is heteroskedasticity in the random estimator and that the random estimator is inefficient. The Breusch-Godfrey LM test provides that there is serial autocorrelation in the panel model, in which the p-value is 0 that the random estimator is inefficient. Through the Global Moran's I test, LM-error test and LM-lag test, it is found that there is spatial autocorrelation on both spatial error and spatial

Table 5.10 Test Results for Panel Model and Spatial Models

Panel:

$$logP_{it} = \alpha_0 + a_1 logTAX_{it} + a_2 IR_{it} + a_3 Dist_{air} + +a_4 Dist_{CBD} + d_1 Region + d_2 Year$$

Spatial:

$$logP_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logTAX_{it} + a_2 IR_{it} + a_3 Dist_{air} + +a_4 Dist_{CBD} + \varepsilon_{it}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$$

	Random	SAC	SAR	SEM	SDM
Tax	1.121*** (25.31)	1.082 (16.58)	1.066*** (16.78)	1.116*** (16.48)	0.941*** (5.68)
Central Bank Interest Rate	-11.19*** (-4.31)	-10.75*** (-2.79)	-10.65*** (-2.93)	-10.7*** (-2.67)	-1.49 (-0.21)
Distance to Beijing Capital Airport (km)	2.38E-07 (0.06)	1.66E-06 (1.21)	1.61E-06 (1.22)	1.75E-06 (1.28)	3.48E-07 (-0.10)
Distance to CBD (km)	-6.79E-06** (-2.35)	-5.4E-06*** (-5.14)	-5.34E-06*** (-5.19)	-5.43E-06*** (-5.04)	-3.08E-06 (-0.97)
Rho(ρ)	-	0.00775 (0.46)	0.0112*** (4.17)	-	0.0522** (2.18)
Lambda(λ)	-	0.00624 (0.20)	-	0.0198*** (3.71)	-
Sigma(σ)	-	0.196*** (18.16)	0.196*** (18.17)	0.195*** (18.17)	0.192*** (18.06)
Constants	2.383*** (12.57)	2.168*** (9.22)	2.183*** (10.10)	2.113*** (8.78)	1.879*** (5.79)
Adjusted r2	0.707	0.697	0.697	0.695	0.939
VIF	1.44	-	-	-	-
Hausman p-value	0.02 1	-	-	-	-
Breusch-Godfrey LM p-value	105.4 0	-	-	-	-
Breusch-Pagan p-value	94.9 0	-	-	-	-
Global Moran's I p-value	0.134 0.01	-	-	-	-
LM-Error Test p-value	6.28 0.01	-	-	-	-
Robust LM-Error Test p-value	4.38 0.04	-	-	-	-
LM-Lag Test p-value	15.85 0	-	-	-	-
Robust LM-Lag Test p-value	13.95 0	-	-	-	-
AIC	-	0.081	0.086	0.072	1.07
Wooldridge LM p-value	-	4.32 0.04	4.32 0.04	4.32 0.04	5.36 0.02
Breusch-Pagan p-value	-	95.5 0	97.34 0	91.58 0	147.1 0

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

Breusch–Pagan test is used to test for heteroskedasticity in the model;

Breusch-Godfrey LM test is used to test for serial correlation;

Moran's I tests for the presence of spatial autocorrelation of residuals, the value is between 1 and −1; positive Moran's I means values in neighbouring positions tend to cluster; negative Moran's I means values are interspersed; zero of Moran's I, there is no spatial autocorrelation, means the data are randomly distributed.

Spatial error: the error terms across different spatial units are correlated.

Spatial lag: the dependent variable y in place i is affected by the independent variables in both place i and j.

Lagrange Multiplier Diagnostics (LM): LM-Error Test and LM-Lag Test determines the type of spatial dependence - spatial error or spatial lag (Robust tests used to find a proper alternative, only use robust forms when BOTH LMerror and LMlag are significant). If p-value of LM less than 0.05 indicates there are spatial autocorrelation on error or lag.

Table 5.11 Test Results for Dynamic Panel Model and Dynamic Spatial Models

Panel:

$$logP_{it} = \alpha_0 + \tau logP_{it-1} + a_1 logTAX_{it} + a_2 IR_{it} + a_3 Dist_{air} + +a_4 Dist_{CBD} + d_1 Region + d_2 Year$$

Spatial:

$$logP_{it} = \alpha + \tau logP_{it-1} + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logTAX_{it} + a_2 IR_{it} + a_3 Dist_{air} + +a_4 Dist_{CBD} + \varepsilon_{it}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$$

	Fixed	SEM	SDM
Lag(1) House Price	0.825*** (22.36)	0.823*** (20.64)	0.866*** (23.59)
Tax	0.248*** (4.88)	0.249*** (4.63)	0.116 (1.33)
Central Bank Interest Rate	-7.686*** (-4.00)	-6.587*** (-2.76)	-5.789 (-1.62)
Distance to Beijing Capital Airport (km)	1.17E-07 (0.17)	6.66E-07 (0.94)	2.91E-07 (0.17)
Distance to CBD (km)	-1.89E-06*** (-3.41)	-1.47E-06** (-2.45)	-1.29E-06 (-0.85)
Rho(ρ)	-	-	0.084*** (4.36)
Lambda(λ)	-	0.0218* (1.91)	-
Sigma(σ)	-	0.099*** (18.16)	0.091*** (17.93)
Constants	0.762*** (5.75)	0.61*** (3.26)	0.727*** (4.06)
Adjusted r2	0.92	0.899	0.848
VIF	2.18	-	-
Hausman p-value	20.89 0	-	-
Breusch-Godfrey LM p-value	4.92 0.03	-	-
Breusch-Pagan p-value	26.18 0	-	-
Global Moran's I p-value	0.297 0	-	-
LM-Error Test p-value	30.9 0	-	-
LM-Lag Test p-value	1.76 0.18	-	-
AIC	-	0.014	2.74
Wooldridge LM p-value	-	24.82 0	23.18 0
Breusch-Pagan p-value	-	19.62 0	158.3 0

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

Breusch–Pagan test is used to test for heteroskedasticity in the model;

Breusch-Godfrey LM test is used to test for serial correlation;

Moran’s I tests for the presence of spatial autocorrelation of residuals, the value is between 1 and −1; positive Moran’s I means values in neighbouring positions tend to cluster; negative Moran’s I means values are interspersed; zero of Moran’s I, there is no spatial autocorrelation, means the data are randomly distributed.

Spatial error: the error terms across different spatial units are correlated.

Spatial lag: the dependent variable y in place i is affected by the independent variables in both place i and j.

Lagrange Multiplier Diagnostics (LM): LM-Error Test and LM-Lag Test determines the type of spatial dependence - spatial error or spatial lag (Robust tests used to find a proper alternative, only use robust forms when BOTH LMerror and LMlag are significant). If p-value of LM less than 0.05 indicates there are spatial autocorrelation on error or lag.

lag. According to the AIC result, the spatial error model (SEM) is a compatible model in the dynamic spatial analysis. In the SEM model, the result provides that the spatial autocorrelation coefficient of λ is 0.02. This means house prices are influenced by the neighbouring unobserved characteristics significantly and positively.

When adding the lag (1) house prices variable, the investigation establishes dynamic models to test the spatial heterogeneity for Model 3 (Table 5.11). Through the Global Moran's I test, the LM-error test and the LM-lag test, it is found there is spatial autocorrelation on spatial error. In terms of AIC, SEM is an efficient model. The results illustrate that the house prices of the previous year influence the house price by 0.82% positively and significantly. This means house prices in neighbouring regions spill-over more in times of increasing neighbouring house prices. This finding is in line with a previous study (Pijnenburg, 2017). Breusch-Pagan Test indicates remaining heteroskedasticity in the residuals.

Table 5.12 and Table 5.13 test the influences of the unbanning population on the house prices (Model 4). Results of the Hausman Test illustrate that random effect is appropriate for this model based on p-value is 1. The Breusch-Pagan Test shows the p-value is below 0.05, which means there is heteroskedasticity in the random estimator and that the random estimator is inefficient. The Breusch-Godfrey LM test provides there is serial autocorrelation in the panel model, which p-value is 0 that random estimator is inefficient.

Through the Global Moran's I test, the LM-error test and the LM-lag test, the investigation found there is spatial autocorrelation on spatial lag. The spatial lag model (SAR) is a compatible model in the spatial analysis. In SAR model, the urban population leads to the increase in house price by 7.36% significantly. The hypothesis H2 is rejected. This result is similar to Zhang et al. (2015) and Chow et al. (2016), which means the urban population influence house prices positively and significantly in Beijing. This finding is in line with Alonso (1964), who provides population is a significant factor in the economic analysis, because the population changes the demand for the number of houses. The investigation result demonstrated the increasing demand that occurs as a result of migration to regions where house prices are comparably low results in an increase in house prices. The results provided that the distance from district to CBD influenced the house price significantly and negatively; which means the closer the house location is to CBD, the higher the price of a house will be. This finding is in line with 'the concentric zone' (Burgess, 1925). The central bank interest rate influence house price significantly and negatively by -9.12%. This in line with Li and Chand (2013), which means the central bank interest rates influence house prices

Table 5.12 Test Results for Panel Model and Spatial Models

Panel:

$$logP_{it} = \alpha_0 + a_1 logUP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$$

Spatial:

$$logP_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logUP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$$

	Random	SAR	SDM
Urban Population	7.742*** (24.76)	7.362*** (16.15)	6.272*** (6.65)
Unemployment Rate	-0.0521 (-0.30)	-0.0482 (-0.20)	-0.0163 (-0.04)
Central Bank Interest Rate	-9.596*** (-3.00)	-9.125** (-2.00)	-9.429 (-0.89)
Distance to Beijing Capital Airport (km)	2.38E-07 (0.05)	1.60E-06 (1.22)	1.10E-06 (-0.30)
Distance to CBD (km)	-6.79E-06** (-2.05)	-5.35E-06*** (-5.25)	-2.78E-06 (-0.88)
Rho(ρ)	-	0.0112*** (4.17)	0.0595** (2.39)
Sigma(σ)	-	0.194*** (18.17)	0.189*** (18.00)
Constants	-7.899*** (-7.15)	-7.599*** (-4.85)	-5.859*** (-3.34)
Adjusted r2	0.675	0.376	0.921
VIF	1.77	-	-
Hausman p-value	0.021 1	-	-
Breusch-Godfrey LM p-value	111.1 0	-	-
Breusch-Pagan p-value	90.1 0	-	-
Global Moran's I p-value	0.119 0.02	-	-
LM-Error Test p-value	4.96 0.03	-	-
Robust LM-Error Test p-value	3.3 0.07	-	-
LM-Lag Test p-value	15.9 0	-	-
Robust LM-Lag Test p-value	14.2 0	-	-
AIC	-	0.086	1.41
Wooldridge LM p-value	-	2.85 0.09	4.86 0.03
Breusch-Pagan p-value	-	92.1 0	149.1 0

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

Breusch–Pagan test is used to test for heteroskedasticity in the model;

Breusch-Godfrey LM test is used to test for serial correlation;

Moran's I tests for the presence of spatial autocorrelation of residuals, the value is between 1 and −1; positive Moran's I means values in neighbouring positions tend to cluster; negative Moran's I means values are interspersed; zero of Moran's I, there is no spatial autocorrelation, means the data are randomly distributed.

Spatial error: the error terms across different spatial units are correlated.

Spatial lag: the dependent variable y in place i is affected by the independent variables in both place i and j.

Lagrange Multiplier Diagnostics (LM): LM-Error Test and LM-Lag Test determines the type of spatial dependence - spatial error or spatial lag (Robust tests used to find a proper alternative, only use robust forms when BOTH LMerror and LMlag are significant). If p-value of LM less than 0.05 indicates there are spatial autocorrelation on error or lag.

Table 5.13 Test Results for Dynamic Panel Model and Dynamic Spatial Models

Panel:

$$logP_{it} = \alpha_0 + \tau logP_{it-1} + a_1 logUP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$$

Spatial:

$$logP_{it} = \alpha + \tau logP_{it-1} + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logUP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$$

	Fixed	SEM	SDM
Lag(1) House Price	0.847*** (21.42)	0.842*** (20.13)	0.867*** (23.10)
Urban Population	1.502*** (3.96)	1.546*** (3.87)	0.918* (1.81)
Unemployment Rate	0.154 (1.16)	0.161 (1.24)	0.282 (1.41)
Central Bank Interest Rate	-4.789* (-1.92)	-4.724* (-1.95)	-2.880 (-0.55)
Distance to Beijing Capital Airport (km)	1.14E-07 (0.17)	1.74E-07 (0.25)	1.75E-07 (0.10)
Distance to CBD (km)	-1.76E-06*** (-3.07)	-1.74E-06*** (-3.08)	-1.21E-06 (-0.80)
Rho(ρ)	-	-	0.0995*** (5.58)
Lambda(λ)	-	0.000768 (-0.27)	-
Sigma(σ)	-	0.103*** (18.17)	0.0909*** (17.83)
Constants	-2.103** (-2.35)	-2.201** (-2.40)	-1.898** (-1.96)
Adjusted r2	0.916	0.916	0.745
VIF	2.42	-	-
Hausman p-value	15.1 0	-	-
Breusch-Godfrey LM p-value	13.8 0	-	-
Breusch-Pagan p-value	27.03 0	-	-
Global Moran's I p-value	0.35 0	-	-
LM-Error Test p-value	42.7 0	-	-
LM-Lag Test p-value	1.56 0.21	-	-
AIC	-	0.012	3.94
Wooldridge LM p-value	-	13.8 0	9.37 0
Breusch-Pagan p-value	-	25.8 0	158.9 0

** p<0.10 ** p<0.05 *** p<0.01*

T-statistic are in parenthesis

Breusch–Pagan test is used to test for heteroskedasticity in the model;

Breusch-Godfrey LM test is used to test for serial correlation;

Moran's I tests for the presence of spatial autocorrelation of residuals, the value is between 1 and −1; positive Moran's I means values in neighbouring positions tend to cluster; negative Moran's I means values are interspersed; zero of Moran's I, there is no spatial autocorrelation, means the data are randomly distributed.

Spatial error: the error terms across different spatial units are correlated.

Spatial lag: the dependent variable y in place i is affected by the independent variables in both place i and j.

Lagrange Multiplier Diagnostics (LM): LM-Error Test and LM-Lag Test determines the type of spatial dependence - spatial error or spatial lag (Robust tests used to find a proper alternative, only use robust forms when BOTH LMerror and LMlag are significant). If p-value of LM less than 0.05 indicates there are spatial autocorrelation on error or lag.

negatively in Beijing. The SAR model provides estimates of the parameters ρ, which is the spatial autocorrelation coefficient of neighbouring dependent variable. In Table 5.12, the spatial autocorrelation coefficient of ρ is 0.011 in SAR. These means the house price is influenced by the neighbouring house price by 0.011% significantly and positively. Thus, H1 is rejected.

In respect to adding the lag (1) house prices variable, it is found that spatial autocorrelation of spatial lag house prices is not significant. However, the house prices of the previous year influence the house price by 0.84% positively and significantly. This means house prices in neighbouring regions spill-over more in times of increasing neighbouring house prices. The Breusch-Pagan Test indicates remaining heteroskedasticity in the residuals.

5.5.2 Marginal Effects and Partitioning Spill-Over Effects

LeSage and Pace (2010) provide that the empirical results of spatial models are analysed by direct effects, indirect (spill-over) effects and total effects in the further research. The reason is due to "the change in a single observation (region) associated with any given explanatory variable will affect the region itself (a direct impact) and potentially affect all other regions indirectly". Accordingly, Table 5.14 and Table 5.15 provide the results of partitioning spill-overs effects in the empirical analysis.

The partitioning methodology, which is introduced by LeSage and Pace (2010), illustrates how to analyse the effects of characteristics of low order and high order neighbouring region (Figure 5.3) on the region being observed. In this investigation, the coefficients of direct and indirect effects for neighbourhood orders are divided into five segments, which are $W_{(0)}$, $W_{(1)}$, $W_{(2)}$, $W_{(3)}$, $W_{(4)}$. The estimated coefficients of indirect effects for $W_{(0)}$, are zero. Because the zero-order neighbourhood means there is no neighbourhood for this factor. The other orders of neighbourhood indirect effects are not zero. Similar explanations of this condition are referred in the previous studies (Autant-Bernard and LeSage, 2011; LeSage and Pace, 2010). Elhorst (2014) illustrated that the direct effects from partitioning depict a process of spatial feedback effects. The direct effects and indirect effects of partitioning provide the influences of factors from immediate neighbours to the subordinate neighbours (e.g. from $W_{(1)}$ to $W_{(5)}$).

Klugman, Panjer, and Willmot (2012) suggest that the statistic of the likelihood ratio test is an appropriate method to choose the best fit models for testing spill-over effects. In this chapter, the likelihood ratio test of SDM model is 36.712, which indicates that the best fit spill-over model is SDM. The Spatial Durbin model (SDM) focuses on the influences of neighbouring explanatory variables of the previous year on the house price. According to the null hypothesis of SDM, λ equals to zero so that the neighbouring unobserved characteristics of the previous year are removed. The SDM model estimates the parameters ρ, which is the autocorrelation coefficients of neighbouring house price of the previous year.

The results show that the major influences of the factors are from direct effects. This means the influences of the factor derive from its own location significantly. For instance, in Table 5.15, 75.6% of direct effects for GDP influence house prices in first-order neighbouring regions. The calculation of direct effects is 1 – 0.338/1.386 = 75.6%; 0.338 refers to indirect effects and 1.386 refers to total effects. Otherwise, the indirect effects of GDP on house prices in first-order neighbouring regions is 24.4%. This means the influences of GDP on house prices originating from the other order neighbouring regions is 24.4%. However, in Table 5.15, the direct effects of GDP is 24% in the second-order neighbours, $W_{(2)}$. This condition provides that the house prices achieve more feedback effects from the other neighbours. There is an interpretation that the second order neighbours are the most influenced by the GDP factor; when compared to the rest of the other order neighbours. Based on the results, this study rejects the hypothesis H3, H4, H5, H6 and H7, which denotes the average wage of staff and workers of real estate have spill-over effects in Beijing; the income of residents have spill-over effects in Beijing; the taxes and other charges on principal business of enterprises for real estate development have spill-over effects in Beijing; the unemployment rate have spill-over effects in Beijing and the urban population have spill-over effects in Beijing. These results are in line with the previous studies (Ge and Wu, 2017; Shen and Liu, 2004; Gan et al., 2012; Harris et al., 2013; Garriga et al., 2017), which suggest that the facotrs of average wage, income, tax, unemployment rate and population influence house prices in China. However, these studies have not contained the spill-over effects of these factors on house price. The results implicated average wage, income, tax, unemployment rate and population changed the spatial pattern of Beijing house price, so that directly and indirectly affect the house price in different areas of Beijing. Overall, the direct effects derive from alternative order neighbours, which indicates house prices are affected form the neighbouring regions significantly. Meanwhile, house prices are affected by the other neighbouring factors significantly as well. The variables of the unemployment rate and central bank interest rate are not detected to be significant. The variable of building starts is significant in the second order. The other variables are significant across all orders. Previous

Table 5.14 Test Results for Summary of Indirect (spill-overs) Effects in SAR Model

	Total				Indirect			
	W(1)	W(2)	W(3)	W(4)	W(1)	W(2)	W(3)	W(4)
Average Wage	1.565***	1.649***	1.635***	1.642***	0.0764	0.0713	0.0142	0.0065
GDP	1.590***	1.681***	1.659***	1.666***	0.0751	0.092	0.0135	0.0059
Tax	1.066***	1.125***	1.113***	1.117***	0.0509	0.0362	0.0092	0.0038
Urban Population	7.362***	7.781***	7.683***	7.713***	0.349	0.382	0.0631	0.0278
Unemployment Rate	-0.0482	-0.0524	-0.0513	-0.0516	-0.0023	-0.0003	-0.0004	-0.0002
Central Bank Interest Rate	-12.02***	-12.71***	-12.55***	-12.61***	-0.568	-0.695	-0.102	-0.044

Table 5.15 Test Results for Summary of Indirect (spill-overs) Effects in SDM Model

	Total				Indirect			
	$W_{(1)}$	$W_{(2)}$	$W_{(3)}$	$W_{(4)}$	$W_{(1)}$	$W_{(2)}$	$W_{(3)}$	$W_{(4)}$
Size of Building Started	0.248	0.905*	0.372	0.538**	0.0796	0.316	0.128	0.071
Average Wage	1.309***	1.369***	1.448***	1.345***	0.420**	0.478	0.497***	0.176
GDP	1.386***	1.460***	1.463***	1.351***	0.338	1.108***	0.355**	0.066
Tax	0.941***	0.902***	0.960***	0.884***	0.205	0.425	0.447	0.075
Urban Population	6.272***	7.703***	6.686***	6.419***	1.548	5.231***	1.730**	0.086
Unemployment Rate	-0.016	-0.093*	-0.02	-0.03	-0.004	-0.006	-0.005	-0.004
Central Bank Interest Rate	-11.38	-16.43	-8.768	-6.524	-2.776	-1.247	-2.128	-0.32

studies (Yang, Noah, and Shoff, 2015) show that the results of significant levels of the partitioned indirect effects in the second order are higher than those of the other order neighbours, which are referred to in the complicated estimation process in Spatial Durbin Model. The results denote that the significance of the partitioned spill-over effects on urban population and GDP; encourages the house price to increase by 68% and 76% respectively. These factors are the most prominent partitioned spill-over effects in the attributes of the house prices. According to Evans (1973), the trade-off theory provides the residential location choices are depending on the minimise cost and maximise utility. The results of partitioning analyses are appropriately explaining the effects of surroundings, which can approach the utilities.

5.6 Conclusion

This chapter analyses the spatial statistics of house prices in Beijing with the spatial autoregressive model (SAR), spatial Durbin model (SDM), a spatial autoregressive model with autoregressive disturbances (SAC) and spatial error model (SEM). The analyses of spatial characteristics in house price dynamics with spatial dependence, spatial heterogeneity and spill-over effects of explanatory are estimated. While it is well-known that spatial dependence and spatial heterogeneity are important aspects of house price developments, the concept of spatial partitioning has not yet received wide-spread attention. This study confirms that the disposition effect could explain the effects of house price spill-overs across space. The investigation supports the previous spatial studies in China (Chow et al., 2016; Hanink et al., 2012; Harris et al., 2013; Hui and Gu, 2009; Li and Chand, 2013; Liu, 2013; Shi and Lee, 2017; Zhang et al., 2015; Zhang et al., 2018). Spatial and non-spatial panel regressions are both estimated to determine whether overall spatial dependence in house price developments is present. The alternative types of spatial models are applied to estimate the most appropriate model for the analyses. On the aspect of analysing direct and indirect (spill-over) effects, this research examines the influence of direct and indirect partitioning and establishes the effects on property prices of neighbouring characteristics, from immediate neighbours to those further.

The results reveal strong house price spill-overs when the increase in house price, size of building started, average wage, income, tax, and a population of the neighbouring regions is taken into account. The house price spill-overs in Beijing area exist when there is an increase in the population of the neighbouring regions, significant upper house price spill-overs are detected in terms of increasing house prices in the neighbouring regions. This result is similar to Zhang et al. (2015) and Chow et al. (2016), which means the urban population influence house prices positively and significantly in Beijing. This finding is in line with Alonso (1964), who provides the population is a significant factor in the economic analysis, because the population changes the demand for the number of houses. Regarding the theory of 'the concentric zone' (Burgess, 1925), the development of ideal construction of the city expands from its CBD. The workers live near CBD aims to easy access to their work. Thus, the demand for house surrounding CBD is high, which causes the increase in house price. The findings of this analysis are also in line with Burgess's theory (1925) that the distance from district to CBD influenced the house price significantly and negatively. This encourages the regulators of Beijing housing market to establish the rational distribution of fixed assets effectively deter the unstable house price variation referred to the population changes.

The differences in household income cause changes in residential location and house prices based on the 'sector theory' (Hoyt, 1939). This result is in line with Shen and Liu (2004). The income significantly influences the house price in Beijing and changes the distribution of house prices. This investigation provides a similar result to Hoyt's theory (1939), which the average wage of employees in the real estate market leads to an increase in house price. This finding is also in line with the theory of 'the concentric zone' (Burgess, 1925), which presents the high-income group 'who have escaped from the area of deterioration' changes the demand of residential location. This encourages the regulators of Beijing housing market to establish the subsidiary CBD in Beijing in order to arrange rational distribution of fixed assets.

Evans (1973) found that there is an equilibrium relationship between the density and revenue of houses in 'the theory of the supply of space'. Thus, even though there is enough space for construction, the irrational density of buildings leads to lower revenues of the house. Size of building starts, which instead of the supply of houses, influences house prices positively. This result is in line with Hanink et al. (2012) and Zhang et al. (2018) who provide house starts is a potential determination of new construction rate which reflects the supply of housing market in Beijing. However, the result is not very significant. The result is similar to Evans (1973), who suggests a rational space and density of constructions are significant to households. Thus, it encourages the regulators of Beijing housing market to control the building permits and continue updating the policy of construction so that rationally monitor the supply of houses.

The research found the taxes and other charges on principal business of enterprises for real estate development lead to an increase in house price significantly. This result is similar to the previous studies (Li and Chand, 2013; Liu, 2013), which means the taxes and other charges on principal business of enterprises for real estate development influence house prices negatively and significantly in Beijing. Based on the trade-off theory (Evans, 1973), the maximum utility of the household is the objective of the choice of location. The increasing tax added the costs of construction, and then the developers will increase the house selling price so that balance the costs. When the household considers the house price, they will change the location of living so that the patterns of residential location changes. Thus, it encourages the regulators of Beijing housing market to control the tax rates, so that have a rational distribution of constructions.

The results of partitioning analyses are appropriately explaining the effects of surroundings, which can approach the utilities. Because of loss aversion, homeowners who intend to sell their properties will not lower their asking price, even when they see house prices declining in neighbouring regions. Loss aversion reduces the number of transactions in the housing market and, reduces the amount of house price spill-over. Results of this study are similar to previous findings (Anenberg, 2011; Engelhardt, 2003; Genesove and Mayer, 2001) with regards to loss aversion in the housing market. This result is also in line with the previous studies (Yang, Noah, and Shoff, 2015), who show that the results of significant levels of the partitioned indirect effects in the second order are higher than those of the other order neighbours, which are referred to in the complicated estimation process in Spatial Durbin Model. Thus, it is suggested that the regulators of Beijing housing market should monitor the economic factors and population in the different order regions in order to adjust the house prices.

The evidence is found for spatial dependence of house prices: house prices in one region are influenced by the house prices in neighbouring regions, positively and significantly in Beijing. The evidence is found for spatial heterogeneity of house prices across space: house price spill-over is greater in neighbouring regions when neighbouring house prices are increasing than when neighbouring house prices are declining. The evidence is found for spatial spill-over effects of explanatory factors: increases of the average wage, income, tax, urban population and house price of last year increase the house price positively in neighbouring regions; a decrease of unemployment drives down the house prices in neighbouring regions. These factors have spill-over effects across space.

From the theoretical standpoint, these findings are likely to contribute to the theory of “the concentric zone’ Burgess (1925) that the information will expand radially from its central place or the city leading to information asymmetries in the surroundings. Consistent with this view, the findings reveal that the house prices in Beijing have a geographical variation and expand radially from CBD. This encourages the city planner of Beijing to simulate the regulation of the United States, which predicts the future pattern of land use in order to decide the optimal distribution of fixed assets investments. The rational distribution of fixed assets effectively averse the unstable house price variation referred to the information asymmetries.

This investigation is the first study to provide the partitioning spill-over effects on house prices based on the regional information asymmetries. In the findings, the significance of the partitioned spill-over effects on urban population and GDP are in the second-order surrounding regions. This result is consistent with and contributed to the ‘sector theory’ (Hoyt, 1939), which the differences in household income cause the changes of residential location and house prices. Thus, it is valuable information for the regulators of real estate market. Because the appropriate distribution of submarket of CBD reduces the degree of income differences, so that decreases the geographical house price variation.

Chapter 6 The Uncertainty of House Prices and Real Options in China

6.1 Introduction

Over the last decades, there is a significant boom in China's real estate market with rapid urbanisation and economic prosperity. While how to purchase valuable land vacant and maximise the shareholder value is a serious problem for the investors. Developing land is analogical to exercise a financial option (Tsekrekos and Kanoutos, 2013 and Razak et al., 2018). However, it is illustrated that the landowners are unable to determine the timing of land development and the uncertainty about the underlying house price on the vacant land in the financial markets (Chiang et al., 2006 and Barbopoulos et al., 2019). The previous studies suggest that the real options theory on land development has denoted several advantages in the real estate market (Capozza and Sick 1991; Cunningham, 2006; Myers, 1977; Oppenheimer, 2002; Quigg, 1993; Shilling et al., 1985; Titman, 1985; Zeng and Zhang, 2011). The value of management or land flexibility determines the value of real options under uncertainty.

There are limited literatures applied real options in emerging market, such as China's real estate market (Huang and Rong, 2017; Hui and Fung, 2009; Li et al., 2014; Shi et al., 2015; Tang and Wang, 2017; Wang et al., 2016; Zeng and Zhang, 2011). The real options theory application in China's real estate market is valuable to explore. Because the added complication is that various control policies, most of which are administrative and quite volatile, are always affecting China's real estate market (Wang et al., 2016). The Chinese real estate market is characteristised by the incomplete information which influences the land development of land in the urban city (Tang and Wang, 2017). The factors influencing the public rental housing fraud are analysed in the real estate market in China (Zeng et al., 2017). The uncertainty of apartments' physical attributes, firms' financial position and other economic conditions influencing apartment price is analysed by Shi et al. (2015). The uncertainty of the real estate market in China should be explained in an appropriate method based on China's real estate market characteristics.

It is recommended to estimate the application of real options in the real estate market in China. The land is valued as an option, for which the underlying asset is the construction that could potentially be built on that site. There is considerable evidence, as well as developments in modified models, to support the application of real options in evaluating real estate markets (Hui and Fung, 2009; Quigg, 1993; Schwartz and Trigeorgis, 2004; Titman, 1985; Yamaguchi et al., 2001). This chapter considers this underlying asset of land as neighbouring house prices, neighbouring unobserved characteristics and economic conditions. We evaluate this by real options in a spatial manner, which improves the accuracy of predicting the value of house prices and considers the neighbouring regional house prices.

Previous studies on real options of real estate market focused on the uncertainty of house prices are applied by OLS estimator, which is in the absence of considering the effects of neighbouring regional influences (Cunningham, 2006; Quigg, 1993; Titman, 1985). In this chapter, the effects of price uncertainty on neighbouring regions are considered by the spatial model. The method we employ to accomplish this is the Spatial Durbin Model (SDM), making this the first time that real option predictions have been tested in a spatial manner. Spatial analysis improves the accuracy of predicting the value of house prices and considers the surrounding regions' house prices and their effects on the house prices of a particular region (Muss et al., 2017). The SDM model includes spatial fixed measures, time fixed measures, and spatial and time fixed measures of expected future prices and price uncertainty. To test for the presence of real options in asset prices, the vacant land sales price is regressed on similar measures of future house price uncertainty.

6.1.1 Research Objectives

This chapter investigates real options with the spatial analysis in China's real estate markets. This investigation extends the real options method with the spatial Durbin model (SDM), making this the first study in which real option forecast have been assessed in a spatial case. It measures the degree of price uncertainty by a generalised autoregressive conditional heteroskedasticity (GARCH) model. The Black-Scholes' (1973) pricing model is employed to explore the option premium of land value. This chapter investigates whether the uncertainty about future house prices in neighbouring regions influence investment activity in the current period. It also examines whether the uncertainty about future house prices in neighbouring regions influence land prices. This research explores whether the market house prices in neighbouring regions reflect a premium for optimal development in terms of the likelihood of developing the land.

6.1.2 Summary of Findings and Contribution

The findings suggest that it is more appropriate to employ a spatial model rather than a non-spatial model in the present investigation based on the Lagrange Multiplier (LM) tests. The spatial method improves the accuracy of predicting house prices by considering neighbouring house prices. The results illustrate that neighbouring house prices affected house prices in this region, supporting the idea that house price has a ripple effect (Pijnenburg, 2017). In the Spatial Durbin Model (SDM) analysis of underlying house price, an increase in income equivalent of 1% is associated with a 41.2% rise in house prices. This result is in line with Tang and Wang (2017), who suggest income increases the house price in China. The unemployment rate and CPI is negatively correlated with house prices. Similar empirical results were obtained by Harris et al. (2013) and Farlow (2004), who provides that house prices were higher in cities with increased income and lower CPI and unemployment rates in China. The spatial fixed model is the first time applied in the real options analysis.

The results of implied volatility analysis provide that house price in China has ARCH effects. This result is in line with Wang et al. (2016), who found ARCH effects for house prices in Hangzhou housing market, China. It is also similar to the study of Cunningham (2006), who found ARCH effects for house prices in Seattle. Based on the results, the standard deviation of residential housing market in China ranges from 2.14% to 23.49%, depending on the time series of house prices. This result is in line with Wang et al. (2016), who provide a one-standard-deviation residential housing market in Hangzhou ranges from 13.39 % and 16.51 %.

Regarding the results of uncertainty and timing of land development, the uncertainty delayed land development, as the coefficient of uncertainty was negative (-1.101). This result is in line with Tang and Wang (2017), who suggest the rising housing demand is accompanied by developers' strategic delay of land development in China. It implies that the uncertainty of future information delays the land development in China based on land flexibility. The results also provide the similar results to Wang et al. (2016), who found the uncertainty delay the land development by 42% in Hangzhou, China. Based on the analyses, the results provide that the uncertainty affected land value by 1.82% significantly and positively. The unemployment rate influences the land value by 40.2%, significantly and negatively. These results are in line with Tang and Wang (2017) and Shi et al. (2015), who suggest the uncertainty increases the land value.

Market prices indicate a premium for optimal development of land, which according to our estimates has a mean of 16.28% of the land value. A one-standard-deviation increase in uncertainty reduces the likelihood of development by 1.101%. These results differ from those of previous studies. Wang et al. (2016) found the real-option premium 9.76% in housing market in Hangzhou, China. Yao and Pretorius (2004) found the real-option premium 11.75% in housing market in Hongkong, China. Quigg (1993) found a real-option premium of 6% on undeveloped land that is relative to the deterministic price. Cunningham (2006) posited a one-standard-deviation increase in the vacant land price of 1.6% in Seattle. This research also estimates that standard deviation of real estate asset values in China ranges from 2.14% to 23.49%, which relies on the time series of property prices. Wang et al. (2016) provide a one-standard-deviation residential housing market ranges from 13.39 % and 16.51 % in Hangzhou, China.

This context appropriately solves the agency problem based on investment timing (Jensen and Meckling, 1976). When the shareholder and agents capture the information of surroundings at the same time and plan the investment of options, the information asymmetric and timing of investment are solved in order to establish an optimal capital structure and maximise the shareholder's value. Regarding the evaluation of land price, the increasing one-standard-deviation in price uncertainty raises the land price. If there is a greater level of price uncertainty according to the economic information, then the vacant land will be traded at a premium above discounted future rents in current low capital use.

The results of this study suggest that investors in China's real estate do take note of real options, even in sectors such as new home construction that is highly competitive and economically important. That real options are present in land markets is further evidence for the need to include real options in capital investment models. Real options have wider implications concerning the importance of price stability and the need for consistent government policy to stimulate fixed investment.

Most research in this area has focused on the house price uncertainty in a panel dataset. This approach provides a basis for testing the main expectations of real options with regard to land development: namely, that neighbouring house price uncertainty should delay building activities and increase the value of vacant land. This investigation extends the real options method with the spatial Durbin model (SDM), making this the first study in which real option forecast have been assessed in a spatial case. The evidence of this research links spatial analysis and GARCH analysis, which adds to the overall understanding of house price uncertainty.

This investigation overcomes the prior studies by extended sample with three datasets have been assembled for this investigation: house price files, land price files and GIS files for each location. When they are combined, these records produce a data set of 496 average house prices and average land prices in 31 provinces of China, for the period 2000 to 2015.

Rather than extracting expectations from subsequently reported advantages, this investigation uses the Black-Scholes' (1973) pricing model to explore the option premium of land value, which concerns current stock price, time until option exercise, option striking price, risk-free interest rates and standard deviation. For the conception of real options, the analyses considered market land value as current stock price, future house price as option striking price, and house price volatility as standard deviation in order to determine the land option premium.

6.1.3 Structure of This Chapter

The remainder of the chapter is organised as follows: Section 6.2 formulates the theoretical framework and hypotheses that are tested in this research; Section 6.3 reviews the previous studies in real options; Section 6.4 outlines the methodology and data; Section 6.5 analyses the estimation results; and Section 6.6 presents the concluding remarks.

6.2 Theoretical Framework

6.2.1 Real Options for Land Development

In the real estate markets, the applications of real option theories are divided into two general areas of prediction. Firstly, uncertainty about future house prices decrease investment activity in the current period, i.e. the current building activity. This prediction stems from Jensen's Inequality and the convexity of the profit function in connection with house prices (Titman, 1985). According to Titman (1985), the "profit fiction" for house prices is convex because developers can exchange land capital by accommodating construction structure when house prices increase. The less confident developers become about property prices in the future, the greater the gap will be between future profits derived from building at the actual price and those derived from building at the expected price. Delaying construction may reveal information which will affect future prices and reduce foregone profits due to construction height or more densely at an inappropriate time. In the Titman (1985) framework, uncertainty reduces the building activity of the current period; in the Capozza and Helsley (1990) model, uncertainty reduces the activity of converting agricultural land to housing in the current period. In either case, the more considerable the uncertainty about future house prices, the lower the desire to invest in the current period. In this chapter, the investigation focused on information about future house prices in neighbouring regions to test whether neighbouring price uncertainty affected building activities or not. This research also examined the effect of uncertainty on land development to determine the presence of real options and timing of land development.

The second prediction is that uncertainty about future house prices increases land prices. The land is at a premium; this is similar to a financial option, as this option allows the owner to acquire security at a predetermined price. Thus, landowners retain a call option that affords a right to purchase an optimal building, based on neighbouring house price information in the future, at an exercise price which is equal to the construction costs. In Titman's model (1985), this refers to the right to own a building of optimal height, dependent on house price fluctuations. The Capozza and Helsley (1990) model, in comparison, refers to the right to convert the land from agricultural usage to housing when house prices increase in the future. In both cases, price uncertainty increases land value. Likewise, future house price uncertainty increases the real option of converting land to high-intensity use at a future time. In this chapter, the investigation was concerned with the issue of the landowner having a right to convert the land to housing, depending on increases in neighbouring house prices.

Real options emphasise the uncertainty about future house prices rather than the volatility of house prices in the current period. If there is a chance that future house prices will increase, the value of vacant land would also increase, accommodating the structure of buildings in the future. This chapter examines whether, on balance, developers consider these factors when making decisions about development and the purchase price of land.

6.2.2 Agency Theory

Without the real options approach, the agency problem may be generated by the timing to invest. The agency theory (Jensen and Meckling, 1976) provided that the concerted contract, designated by 'a principal entity and an agent where the latter has legal authority to act for the first', caused conflicts. The agency problem crucially denoted that the agent, which also be a manager, may be accounted for moral hazard, conflict of interests and not acting aligned with the principal's interests. In the case of real estate sector, the principal is represented by the developer of vacant land and the agent is represented by the sales agent. Without the assumption of real options approach, when the developer has made the investment decision first, the objective of developer is to maximise the investment expected net present value (NPV) in terms of achieving the fixed portion of the investment's (NPV). The profits of the agent with sharing rule are settled before bargaining. However, if the developer is encouraged to delay the timing of construction based on the existence of options, the objective of developer is changed to maximize the expected NPV of the claim on the future investment after bargaining. After bargaining, the option to invest still exists. In another word, the timing of construction causes the agency problem (Jensen and Meckling, 1976). For instance, the developer bought vacant land in 2015 and encouraged to finish the building in 2017. In 2016, this developer entrusted a sales agency to sell the units of building with 2% profits of revenues. The expected revenue of constrictions is one million. However, after this bargaining, the developer found that there will be 1.5 million revenues of the building if the construction will be sold in 2018. The developer decided to delay the construction time, so that achieve the higher profits. Whereas, the agent still gets 2% of revenues which does not maximise the shareholders' value. Real options are the right to buy or sell a physical asset after the company has made an investment decision to purchase that asset (Myers, 1977). In cases of Titman (1985) framework and Capozza and Helsley (1990) model, the more considerable the uncertainty about future house prices, the lower the desire to invest in the current period. Thus, real options approach is appropriate to reduce the agency problem based on the timing of investment.

Banerjee et al. (2014) argued that the agency conflicts occur in terms of the influences of incomplete and asymmetric information on the shareholder maximizing operation of the agent. In the assumption of real options, the investment opportunity is directly managed by the principal, who also be the owner (McDonald and Siegel, 1986). Meanwhile, the agents are perfectly aligned with them (Dixit and Pindyck, 1994). Regarding the previous studies of agency conflicts with real options in the recent, Nishihara and Shibata (2008) extends the model involves the relationship between an audit mechanism and managers' behaviours with bonus-incentives. Shibata and Nishihara (2010) contributed the agency conflicts and real options based on debt financing on investment expenditure. Hori and Osano (2010) provided a model consider the managerial compensation that endogenously illustrated a contingent claim on firms' cash-flows using stock options. However, this investigation established a spatial method, which considered the effects of surrounding house prices and surrounding economic factors, has improved the accuracy of house price uncertainty estimation, in terms of reducing the agent problems of incomplete and asymmetric information. Thus, the optimal contract scheme could be proposed by real options approach with spatial analysis. In this context, this investigation avoids inadequate information from the agent in order to encourage the shareholders to follow the future evolution of investment value so that to achieve the optimal profits.

6.2.3 Predicting House Prices

Pijnenburg (2017) provided that the spatial dependence in house prices is represented as a ripple effect, and that spatial dependence is the movement of house prices between one region and the neighbouring regions. Meen (1999) contended that migration, equity transfer and information asymmetries are the fundamental economic variables affecting house prices and cause the spatial spill-overs of house prices. Information asymmetries may suggest that any new information that is available about the housing market is not communicated immediately to other submarkets, but instead over a period; thus, a ripple effect might appear if the variables that explain house prices themselves show a spatial pattern. Kuethe and Pede (2011) argued that, in the Western USA, the forecasting of one state's house prices could be improved by considering house prices from neighbouring states, further suggesting that prior house prices can influence current house prices in space and time. Holly et al. (2011) also found a dynamic spill-over effect of house prices from neighbouring regions. According to Kohn and Bryant (2010), excessive demand for housing caused house price volatility in the US economy. Therefore, this chapter empoy SDM approach to forecaste the underlying house prices which provides a basis for testing the main expectations of real options with regard to land development. This investigation extends the real options method with the spatial Durbin model (SDM), making this the first study in which real option forecast have been assessed in a spatial case.

From the house price spatial model, the price of housing depends on income, CPI, unemployment rate, population density and the culture of the region. Farlow (2004) suggested that real incomes and interest rates are the essential factors that act as determinants of real house prices. Zhang et al. (2016) found that the income is relative to house prices significantly and positively in China. According to Giussani and Hadjimatheou (1991), there is a positive correlation between income and house prices. Chang et al. (2008) analysed Taipei's housing real estate market through the house price-income and house price-rent state-space model and found a significant relationship between income and house price. Riley et al. (2015) opined that the falling house prices are associated with the increasing unemployment. Geoffrey (2017) examined the way school quality and uncertainty about quality affects house prices. The author concluded that higher school quality raises the value of houses within the catchment area and steepens the gradient, while uncertainty about quality lowers house prices and flattens the gradient. Thus, this investigation added the observable measures of hospitals, museums and libraries to our tests of house prices, which are new independent variables for evaluating house price.

6.3 Literature Review

6.3.1 Real Options Development

Myers (1977) first proposes the 'real options' concept and suggests similarities between the financial options and real options. According to Myers (1977), 'real options' are the right to buy or sell a physical asset after the company has made an investment decision to purchase that asset. An analysis of risk projects was made by Ross (1978) who provides inherent potential investment opportunities so that the theory of real options valuation could be discussed. Trigeorgis (1993) illustrates the seven categories of real options through the proper evaluation of investment alternatives under conditions of uncertainty and differences in flexibility. Meanwhile, Gibson (2001) shows the importance of flexibility for corporate real estate portfolios, in contrast with Trigeorgis (1993). Amran and Kulatilaka (1999) apply option pricing theory and financial market rules to the evaluation of non-trading assets, helping managers make use of their option rights to make management decisions in option areas. There are sixteen aspects of real options applications which contain real estate, summarised by Lander and Pinches (1998). Parthasarathy and Madhumathi (2010) value the project as a perpetual American call option and computed the premium value of the commercial project and found there is a strategic return of 85% to the developers. Regarding the above studies, the real options theory is to associate monetary value referred to the flexibility (Čirjevskis and Tatevosjans, 2015). Dixit and Pindyck (1994) and Trigeorgis (1999) provide that alternative methodologies to better evaluate investment projects in the presence of these managerial flexibilities within the real options theory. Schwartz and Trigeorgis (2004) include classical readings where real options have been applied to several investment projects to account for the value of flexibility where the traditional net present value (NPV) is unable to do so. Trigeorgis (1993) shows alternative roles among several real options embedded in a single project, including the non-additivity principle of their individual values. Lander and Pinches (1998) identify that the lack of mathematical skills, restrictive modelling assumptions, and increasing complexity are the main obstacles to the practical implementation of the real options approach. Hui and Fung (2009) discuss some of the implications of the Williams and Quigg valuation framework in real options as real estate development. Real options have been applied to investment projects to account for the value of flexibility where the traditional DCF is unable to do so (Tsekrekos and Kanoutos, 2013). Once the future information is received and the uncertainties identified, the optimal decision can be made by investment (Fan et al., 2018).

6.3.2 Employment of Real Options in Real Estate Market

Real options analysis has varied applications in real estate markets. Winfree et al. (2002) find that land which is not developed has a significantly higher price through real options analysis. Capozza and Sick (1989) find that options could be used to convert agricultural land into urban land. Subsequently, Capozza and Schwann (1990) apply options to convert land for urban usage. Williams (1991) illustrates the optimal timing for land development and abandonment of the property as well as the optimal density in terms of the presence of uncertainties about price/m^2 and cost/m^2. Quigg (1993) analyses Seattle's real estate transaction data between 1976 and 1979 and found that holding undeveloped land was the equivalent of holding an American-style call option; meanwhile, a land evaluation model with options was also suggested. Capozza and Sick (1994) present the case that agricultural landowners have the option to convert their property into urban land suitable for real estate developments. Their results showed a positive correlation between the land price waiting for conversion and the land rent price. When rental urban land prices become more volatile, the option for agricultural land development became more valuable. Grenadier (1995) shows that the difference between the dynamic and static strategies was the value added by the options embedded. A year later, Grenadier (1996) suggest that the behaviour of real estate markets with option game concepts linked the investment timing in strategic equilibrium to increases or reductions in development activity. Quigg (1995) finds that perpetual American options exceed the value of rent expected for a building at the decision date, with a method of valuing the option to wait before developing the land. Patel et al. (2001) and Yamazaki (2001) analyse land prices by using the empirical testing of premium option in real estate, favouring the application of real options theory. In 2002, Oppenheimer (2002) proposes real options models in real estate evaluations with a review of conditions and methods. Subsequently, there is a case study of a house investment in Rio de Janerio which shows the proposed values of managerial flexibilities and improved risk management by identifying the optimal strategy and timing for construction phases, in order to examine the application of real options analysis (Rocha et al., 2007). Karami and Farsani (2011) illustrate that the real options method shows lower EC for a failed project than those who merely use the net present value method. Zeng and Zhang (2011) provide a literature review of real options covering 30 years of research. It is suggested that the discounted cash flow method is essential to value the real options of real estate (Makhudu, 2011).

For China, Wang et al. (2016) consider the existence of policy intervention of land in China and introduce policy uncertainty into a real options framework. The authors examine the determinants of timing of land development empirically, using a sample of 783 residential projects in Hangzhou, China from 2005 to 2011 and provide a theoretical explanation for the land development decision. The monetary policy indices are regarded as a measurement of policy environment, and results provide when the expected policy is positive, a one-standard-deviation increase in the volatility of M2 change rate and interest rate lowers the likelihood of development by 13.39 % and 16.51 %. However, market uncertainty fails to meet the prediction of real options, which indicates that developers in China focus more on policy uncertainty rather than market uncertainty in exercising their real options. They further find that in the face of declining demand, price volatility significantly accelerates land development. Tang and Wang (2017) suggest the rising housing demand is accompanied by developers' strategic delay of land development in China. This paper uses a dataset of residential projects from the City of Hangzhou, China, and finds incomplete information undermines the acceleration effect of competition on development timing. This delay effect disappears when the project is developed in multi-phases. Shi et al. (2015) investigate real estate development firms' pricing behaviours in Beijing, China during the period 2006–2008. They find that real estate development firms apply real options theory for new apartment price setting at the presale stage, having regard also to apartments’ physical attributes, firms’ financial position and other economic conditions. Zeng et al. (2017) consider the public rental housing fraud is an essential problem since the central government decided on the large-scale construction of affordable housing in 2010. They provide marital status, education, occupation, family size and household per capita disposable income, current situation cognition, audit difficulty cognition, and punishment cognition will increase or decrease the probability of fraud. It seems like there is no relationship between house price and the probability of fraud. However, the authors applied real options to analyse the information of the real estate market in China. Li et al. (2014) analyse the private sector's provision of public rental housing (PRH) in China. This paper fills the gap between a privately-owned PRH provision mode and a real option-based valuation model. The authors find the increasing the average rent of PRH buildings is found to be the most effective measure to enhance the ENPV indicator. This prior enrich the application of real options in the real estate market in China. Therefore, the uncertainty of the real estate market in China should be explained in an appropriate method based on China's real estate market characteristics.

Real options encourage investors to pay attention to strategical consideration in the real estate market. Real options require the landowner to identify the options depending on the decisions and to determine under which conditions the option will be exercised. It leads to a flexible investment style in which investors occur optimally as economic uncertainty unfolds.

6.4 Methodology

6.4.1 Model of Land Development

This investigation calculates the option premium of land using the Black-Scholes pricing formula for call options, based on the work of Titman (1985) and Quigg (1993), who suggested that vacant land can be treated as a call option. The Black-Scholes pricing formula considers the ensuing variables: current underlying price, options strike price, time until expiration, implied volatility and risk-free interest rates. The specifications for the Black-Scholes pricing formula are as follows:

$$C = SN(d_1) - N(d_2)Ke^{-rt} \tag{6.1}$$

$$d_1 = \frac{\ln\left(\frac{S}{K}\right) + (r + \frac{S^2}{2})t}{s * \sqrt{t}} \tag{6.1.1}$$

$$d_2 = d_1 - s * \sqrt{t} \tag{6.1.2}$$

Where:
C = call premium
S = current stock price
t = time until option exercise
K = option striking price
r = risk-free interest rate
N = cumulative standard normal distribution
e = exponential term
s= standard deviation
ln = natural log

Cunningham (2006) provides a framework to explain the decision on land development in terms of the future use of land. The profit of new land development is specified as:

$$\pi = P_i - C_i - R \tag{6.2}$$

where, π is the profit of a new development of land. P_i is the house price at location i. C_i is cost of house location i. R is the land rent. In order to deal with the optimum amount of capital at location i, the investigation estimates the equilibrium land rent, which is R_i. When the profit is equal to zero, the modified formula of land rent is written as:

$$R_i = P_i - C_i \tag{6.2.1}$$

When the land value at location i, which has newly established houses, is more than the value of land as it is currently used, the land will be developed for housing construction. The landowner makes a decision as below:

$$\text{if } R_i \geq R_{current}, \qquad \text{build}$$
$$\text{if } R_i < R_{current}, \qquad \text{do not build}$$

Regarding the purpose of this model, $R_{current}$ is concerned as the discounted future rent of land. However, if the future house price at location i is uncertain, the optimal land capital, m, will be referred to today's price information. The current house prices in the neighbouring regions have an ability to inform the level of investment in the future. When the market values this information, there should remain a real-option premium, C (Equation 6.1), on undeveloped land. These option premiums may delay the building activity. Accordingly, the modified decision with option premium by landowner is written as:

$$\text{if } R_m \geq R_{current} + C, \qquad \text{build}$$
$$\text{if } R_m < R_{current} + C, \qquad \text{do not build}$$

where R_m represents the land rent at the optimal land capital. Thus, the increase of option premium delays the building activity, while the decrease of option premiums encourages the land development. However, to successfully determine the presence of real options premium requires predictions of underlying house prices and examinations of uncertainty about underlying house prices.

6.4.2 Forecasted House Prices

The land is appraised to decide whether to develop into a building or to keep in its current usage. If the landowner decides to develop the land into construction, the future building is underlying to the land value. As stated above, the price of the future building is not observable and needs to be estimated. This investigation employs spatial Durbin model (SDM) for this purpose. SDM focuses on the effects of the independent variables in itself location and the surrounding regions. This chapter separates the sample by year (2000-2015) and into the 31 provinces of China (i.e. 16 years × 31 provinces) to improve the predictive power of the coefficients. For the sample, the model regresses the log function of house prices on its influencing factors, as follows:

$$P_{it} = \alpha + \tau P_{it-1} + \rho \sum_{j=1}^{N} W_{ij} P_{it} + \beta_k \sum_{k=1}^{k} X_{itk} + \theta_k \sum_{k=1}^{k} \sum_{j=1}^{N} W_{ij} X_{itk} + \upsilon_{it} \quad (6.3)$$

$$\upsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \upsilon_{it} + \varepsilon_{it} \quad (6.3.1)$$

Here, the vector of independent variables (X) contains gross regional product (GDP), consumer price index (CPI), population density (pop_den), unemployment rate (une_r), number of regular institutions of higher education (num_edu), number of public libraries (num_lib), number of museums (num_muse) and number of healthcare institutions (num_heal). The dependent variable is an N×1 vector incorporating each dependent variable for every spatial element (i=1,…, N) at time t. ρ is the spatial dependence parameter, m the specific region, j_t the time-period-specific effects, iN is an N×1 vector of ones, and X_t is an N×K matrix of K explanatory variables. In the spatial model, the intercept α, the contributions of neighbouring houses (ρ) and neighbouring factor characteristics (θ_K) are allowed to vary by regions across time.

The resulting parameter estimates, which vary by time and district, are used to predict the value of a house in a particular time and province. The specifications for the adjusted house price series are as follows:

$$P'_{it} = \alpha + \tau P'_{it-1} + \rho \sum_{j=1}^{N} W_{ij} P'_{it} + \beta_K \sum_{K=1}^{K} X'_{itk} + \theta_K \sum_{K=1}^{K} \sum_{j=1}^{N} W_{ij} X'_{itk} \quad (6.4)$$

Previous studies, such as Titaman (1985), Quigg (1993) and Cunningham (2006), applied OLS specifications to examining the house price uncertainty. However, this investigation established a spatial method which considers the surrounding house price effects and surrounding economic factor effects in order to improve the accuracy of the resulting house price uncertainty. Therefore, this investigation extends this model by incorporating the spatial Durbin model.

6.4.3 Measuring House Prices Uncertainty

This investigation measures the degree of house price uncertainty employing generalised autoregressive conditional heteroskedasticity (GARCH) model. The house price of one year ahead, P'_{it-1}, is estimated by incorporating with the current house price, P'_{it}, to establish the mean equation of GARCH, which is written as:

$$P'_{it} = \alpha_i + \alpha_{1i} P'_{it-1} + \varepsilon_{it} \quad (6.5)$$

In the formula 4.5, t is the year the house was sold, and i denotes the province. The estimate of price uncertainty is calculated as the one-year moving variance of residuals, which is the variance equation of GARCH, and can be written as:

$$\sigma_{it}^2 = a + \gamma \varepsilon_{it-1}^2 + \theta \sigma_{it-1}^2 \quad (6.5.1)$$

The investors' confidence in the one-year-ahead price forecast is stipulated on the accuracy of price forecasts in the recent past. The estimation of the variance of residuals suggests the developers have additional information that is influencing the price. On the other hand, the factor, which is leading market price, might be recognised more by developers through σ_{it}^2. Thus, the measure, σ_{it}^2, involves the assumption that developers know σ_{it}^2 for the next year. This method declines the error term. Meanwhile, GARCH estimation provides that the price uncertainty, which is σ_{it}^2, rises when the analysis includes the one-year-ahead house price. The variation in uncertainty is reasonable over time and across districts.

The method employed to measure house price uncertainty accords with previous studies (Cunningham, 2006; Schwartz, 2013; Byun and Min, 2013). The future price uncertainty, σ_{it}^2, suggests that developers' confidence in their predicted price forecast depends on the availability of forecast prices in the recent past (Cunningham, 2006). Combining the GARCH model and real options approaches, the investigation employs σ_{it}^2 of GARCH model as house price volatility in the real options approaches. When there are real options, the forecasting model is appropriate to house price analysis. The increase of house price volatility, σ_{it}^2, delays the building activity. Moreover, the house price volatility increases vacant land prices by the future house price.

6.4.4 Other Explanatory Variables

In order to explore the influences of price uncertainty on the development timing, the duration of time (in years) is set at a maximum of two based on regulations governing land development in China. The investigation employs two-years-time as the 'time until option exercise' (t in formula 6.1) in the real options approach. Based on the China land policy, after buying the land, the land must be utilised for building or agriculture land. Thus, in reference to the land parcels, the investigation assumes that the timing of land development is explained by the point when undeveloped land ends when the construction of a building begins.

In the real options model, the investigation involves a ten-year Chinese government bond interest rate, r_t (r in formula 6.1), which is regarded as a risk-free rate in real options model. This ten-year Chinese government bond interest rate measures the cost of capital applied to build houses. According to Cunningham (2006), interest rate could be regarded as a determinant of house demand when referring to private mortgage conditions. Moreover, the author also emphasised that increasing interest rates decrease the discounted present value of future returns. Thus, higher-interest rates produce more profits over short terms than the rents from the future constructed building. The influence of high interest rates on the development timing maintains an empirical question for further research.

In order to explore the real option premium, the investigation involves a factor of future house price uncertainty, ε_{it}^2, in the model of land development timing and the model of the undeveloped land price.

6.4.5 Uncertainty and Timing of Land Development

The previous studies suggest that the proportional hazard model is appropriately employed to examine the effects of house price uncertainty on the timing of land development (Bulan et al., 2009; Cunningham, 2006; Shi et al., 2015). The proportional hazard model examines the function of timing of land development $h(t)$. In other words, the land will 'dies' when a building is constructed on it. The length of time, which is from presale permit to developers to put the houses on the market for sale, depends on the baseline hazard model assumption, $h_0(t)$, and a vector of covariates, Z. Regarding the spatial lags of land prices and explanatory variables, this thesis incorporates the spatial Durbin model into the proportional hazard model, which is specified as:

$$h(t) = h_0(t)\exp(\delta Z) \quad (6.6)$$

where the baseline hazard, $h_0(t)$, is shifted by a vector of covariates, Z. The covariates are specified as:

$$\delta Z = \gamma E[Y'_{it}] + \varphi\sigma_\varepsilon^2 + \rho \sum_{j=1}^{N} W_{ij} L_{it} + \sum_{K=1}^{K} X_{itk}\beta_K + \sum_{K=1}^{K}\sum_{j=1}^{N} W_{ij} X_{jtk}\theta_K \quad (6.6.1)$$

The expected house prices, $E[Y'_{jt}]$, and price uncertainty, σ_ε^2, vary by year t and by province j. The vector of independent variables (X) contains: gross regional product (GDP), consumer price index (CPI), population density (pop_den), unemployment rate (une_r), number of regular institutions of higher education (num_edu), number of public libraries (num_lib), number of museums (num_muse) and number of health care institutions (num_heal). The effect of price uncertainty on the timing of development is estimated by cross-sectional variation.

When real options exist, an increase in house price uncertainty will delay the timing of building activity. The investigation assumes that house price uncertainty does not affect the timing of land development. Thus, the coefficient of φ (in formula 6.6.1) is equal to zero in the null hypothesis. While the price uncertainty delays the timing of land development in the alternative hypothesis, which means φ is less than zero.

6.4.6 Uncertainty and Land Prices

Concerning the test for the existence of real options in land markets, this investigation examines the price uncertainty on transacted land prices. Price uncertainty increases the option premium on land and causes the land to be more valuable with alternative uses than it does for immediate development. To test the presence of price uncertainty, this investigation employs house price uncertainty factor on land values. The model specifies a regression model of vacant land prices. If there is a greater level of price uncertainty according to the economic information, then the vacant land will be traded at a premium above discounted future rents in current low capital use, $R_{current}$. The equation of price uncertainty and land prices can be written as:

$$L_{it} = \alpha + \alpha_1 \varepsilon_{it}^2 + \alpha_2 fpriceh + \alpha_3 GDP + \alpha_4 CPI + \alpha_5 une\_r + \varepsilon \tag{6.7}$$

Here, L is vacant land price, ε_{it}^2 is the uncertainty of house price, fpriceh is predicted future house price, GDP is an index of gross domestic product, CPI is consumer price index and une_r is unemployment rate. When there are real options, the price uncertainty should increase the option premium, C (in formula 6.1). If the parameter estimate of price uncertainty is significantly above t zero, this investigation could reject the null hypothesis that price uncertainty does not affect land values.

6.5 Robustness of Findings

In this sector, the investigation illustrates the results of the estimation and specification tests. Black-Scholes pricing formula considered the variables, including current underlying house price, options strike price of land, time until expiration, implied volatility and risk-free interest rates. These factors will be analysed in the following sections. The summary statistics for variables are provided in Table 6.1.

Table 6.1 Summary Statistics for Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Price	496	3,722.77	3,029.72	854	22300
GDP	496	11,336.02	12,327.25	117.8	72812.55
CPI	496	102.34	2.13	96.7	110.1
Une_r	496	3.60	0.71	0.8	6.5
Pop_den	496	2,275.10	1,411.93	171	6307
Num_edu	496	64.25	36.08	3	162
Num_heal	496	19,014.57	18,239.52	1237	81403
Num_lib	496	92.28	43.92	1	203
Num_muse	496	71.67	56.00	1	312
Size_building	496	5,041.41	3,784.01	33.4	20477.12
VIF	4.38				

Price=house average price (yuan), GDP=gross regional product (100 million yuan), CPI=consumer price index (preceding year=100), une_r=unemployment rate in urban area (%), pop_den=population density of urban area (person/sq.km), num_edu=number of regular institutions of higher education (unit), num_heal=number of health care institutions (unit), num_lib=number of institutions in public libraries(unit), num_muse=number of museums (unit), size_building=floor space of residential buildings completed (10000 sq.m).

6.5.1 Underlying House Prices

The investigation notes that while a variety of spatial models exist (e.g. SEM, SAR), the incorporation of both into a single model (e.g. SDM) has not been previously employed to capture spatial dependence in housing studies. Elhorst (2010) provides guidelines for determining the appropriate model specification, which is followed in the present study. To decide whether panel analysis or spatial panel analysis should be employed, the Lagrange Multiplier (LM) test is employed to determine the appropriate model including non-spatial model (OLS), spatial lag model and spatial error model (see Table 6.2). The LM test is based on the residuals of the OLS model. If the LM tests results provide the rejection of non-spatial model, then the spatial model is the appropriate method to be employed. In the spatial models, if the LM spatial lag test is significant (p-value is less than 0.05), the spatial lag model (SAR) is appropriate to employ. Alternatively, if the LM spatial error test is significant (p-value is less than 0.05), the spatial error model (SEM) is appropriate to employ. When both the LM spatial lag test and the LM spatial error test are significant, the spatial autoregressive model with the autoregressive disturbances model (SAC) is appropriate to employ. Table 6.2 presents the test results (LM classic and robust tests) for the different panel model specifications. Using the classic and robust LM tests, the hypothesis of the non-spatially autocorrelated error term and the hypothesis of no spatially lagged dependent variable were both rejected at the 1% significance level. Overall, these results suggest that it is more appropriate to employ a spatial model rather than a non-spatial model in the present investigation.

This investigation also tests whether the unobserved heterogeneities (spatial and time period fixed effects) are jointly significant by performing likelihood ratio (LR) tests. The hypothesis that the spatial fixed effects are not jointly significant can be rejected for house price (70.1, $p > 0.01$) estimations. Similarly, results showed that the hypothesis that time-period fixed effects are not jointly significant could also be rejected for house price (664.64, $p < 0.01$) estimations. These test results justify the extension of the spatial model with spatial fixed effects and time period fixed effects and are similar to those of the previous study (Mussa et al., 2017), which tested the immigration effects on house prices in the USA. Accompanied by the prior studies of the Chinese housing market, these results are also in line with Zhang et al. (2015) and Chow et al. (2016), which means Beijing house price has a spatial heterogeneity. It implicates the house price in China has spatial dependence and spatial heterogenous. Thus, the results illustrate that neighbouring house prices affected house prices in this region, supporting the idea that house price has a ripple effect (Pijnenburg, 2017).

Since the OLS specification is rejected in favour of spatial models, the investigation proceeds by estimating the SDM model. This research determines whether or not the SDM can be simplified to one or the other (spatial lag or spatial error model) using a Wald test (Elhorst, 2010). Regarding the Wald test and the LR test, results shown in the bottom column of Table 6.3 and Table 6.4, indicate that both the spatial lag and the spatial error tests were rejected in favour of the SDM. It implies that the spatial dependence of house prices is exist. The present investigation will, therefore, employ the SDM model to describe house prices and predict future house prices.

The novelty of the SDM method lies in its ability to disaggregate the marginal (total) effects into direct and indirect effects, as displayed in Table 6.3 and Table 6.4. The first column of each specification records the direct effect which is the impact of changes in determinants on house prices in a particular province. The indirect or spill-over effect, displayed in the second column of each specification, measures the impact of price determinants in a particular province on house prices in surrounding provinces. The total effect is the sum of both direct and indirect effects. It implies the house prices in China has spill-over effects which is in line with Chow et al. (2016), Zhang et al. (2015) and Zhang et al. (2017).

Table 6.2 Test Results for Choosing Between Spatial and Non-Spatial Models

OLS:

$$P_{it} = \alpha + \tau P_{it-1} + a_1 GPD_{it} + a_2 CPI_{it} + a_3 une\_r_{it} + a_4 pop\_den_{it} + a_5 num\_edu_{it} + a_6 num\_heal_{it} + a_7 num\_lib_{it} + a_8 num\_muse_{it} + a_9 size\_building_{it} + \varepsilon_{it}$$

Spatial:

$$P_{it} = \alpha + \tau P_{it-1} + \rho \sum_{j=1}^{N} W_{ij} P_{it-1} + a_1 GPD_{it} + a_2 CPI_{it} + a_3 une\_r_{it} + a_4 pop\_den_{it} + a_5 num\_edu_{it} + a_6 num\_heal_{it} + a_7 num\_lib_{it} + a_8 num\_muse_{it} + a_9 size\_building_{it} + \varepsilon_{it}$$

	log house price		
	Spatial fixed effect	Time-period fixed effect	Spatial and time-period fixed effect
LM spatial lag (classic)	46.93 [0.000]	22.93 [0.000]	34.8 [0.000]
LM spatial error (classic)	70.82 [0.000]	16.69 [0.000]	23.96 [0.000]
Robust LM spatial lag	0.1171 [0.732]	7.012 [0.008]	33.02 [0.000]
Robust LM spatial error	24 [0.000]	0.7752 [0.379]	22.18 [0.000]
Robust LM SAR	21.4 [0.011]	9.84 [0.363]	24.88 [0.003]
Robust LM SEM	27.53 [0.001]	18.28 [0.032]	27.29 [0.001]
LR tests for the joint			70.1
Significance of spatial fixed effects			[0.000]
LR tests for the joint			664.64
Significance of time-period fixed effects			[0.000]

P values are in square brackets.

P=house average price (yuan), GDP=gross regional product (100 million yuan), CPI=consumer price index (preceding year=100), une_r=unemployment rate in urban area (%), pop_den=population density of urban area (person/sq.km), num_edu=number of regular institutions of higher education (unit), num_heal=number of health care institutions (unit), num_lib=number of institutions in public libraries(unit), num_muse=number of museums (unit), size_building=floor space of residential buildings completed (10000 sq.m), i and j=the location of house, t=time.

Table 6.3 presents the results of the house price equation with specifications displaying the SDM results prior to and after controlling for unobserved fixed heterogeneities. The effect of the spatial coefficient, ρ (W∗house price), displayed in the first row of Table 6.3, is highly significant in both specifications, suggesting that this estimation strategy is appropriate. When rents in one region rise (or fall), the house prices in surrounding regions tend to rise (or fall) as well. The methodology splits the "total effect" of the explanatory variables into two parts: the "direct effect" and "indirect effect". Considering first the direct effect in the Spatial Durbin Model, the results suggest that income is positively associated with house price and that unemployment rate is negatively associated with house price. More specifically, the coefficient of income is interpreted as the percentage change in house price, equal to 28.4%. A similar result holds after the research controls for time period fixed effects. An increase in income equivalent of 1% is associated with a 41.2% rise in house prices. This result is in line with Tang and Wang (2017), who suggest income increases the house price in China. Moreover, the unemployment rate and CPI is negatively correlated with house prices. Similar empirical results were obtained by Harris et al. (2013) and Farlow (2004), who found that house prices were higher in cities with increased income and lower CPI and unemployment rates in China.

Table 6.3 House Prices Estimation

$$P_{it} = \alpha + \tau P_{it-1} + \rho \sum_{j=1}^{N} W_{ij} P_{it-1} + a_1 GPD_{it} + a_2 CPI_{it} + a_3 une\_r_{it} + a_4 pop\_den_{it} + a_5 num\_edu_{it} + a_6 num\_heal_{it} + a_7 num\_lib_{it} + a_8 num\_muse_{it} + a_9 size\_building_{it} + \theta_1 \sum_{j=1}^{N} W_{ij} GPD_{jt} + \theta_2 \sum_{j=1}^{N} W_{ij} CPI_{jt} + \theta_3 \sum_{j=1}^{N} W_{ij} une\_r_{jt} + \theta_4 \sum_{j=1}^{N} W_{ij} pop\_den_{jt} + \theta_5 \sum_{j=1}^{N} W_{ij} num\_edu_{jt} + \theta_6 \sum_{j=1}^{N} W_{ij} num\_heal_{jt} + \theta_7 \sum_{j=1}^{N} W_{ij} num\_lib_{jt} + \theta_8 \sum_{j=1}^{N} W_{ij} num\_muse_{jt} + \theta_9 \sum_{j=1}^{N} W_{ij} size\_building_{jt} + \nu_{it}$$

	Spatial Durbin model			Spatial Durbin fixed effects model		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Rho(ρ)	0.462***			0.232**		
	(6.92)			(2.22)		
GDP	0.284***	0.461***	0.745***	0.466***	0.365**	0.831***
	(4.18)	(3.73)	(5.25)	(5.24)	(2.49)	(4.93)
CPI	-1.045	0.865	-0.179	-2.470***	-0.713	-3.182
	(-1.40)	(0.76)	(-0.25)	(-2.65)	(-0.38)	(-1.55)
une_r	-0.209**	-0.486	-0.694**	-0.499***	-0.565*	-1.064***
	(-2.17)	(-1.53)	(-2.04)	(-4.06)	(-1.96)	(-3.06)
pop_den	-0.0181	0.0116	-0.00648	-0.0498	-0.0854	-0.135
	(-0.63)	(0.16)	(-0.08)	(-1.50)	(-0.90)	(-1.29)
num_edu	-0.0292	0.308	0.279	0.0608	-0.665**	-0.604**
	(-0.38)	(1.52)	(1.13)	(0.55)	(-2.30)	(-2.32)
num_heal	-0.00783	0.109***	0.101**	-0.174***	-0.0465	-0.221
	(-0.35)	(3.06)	(2.52)	(-4.15)	(-0.25)	(-1.12)
num_lib	-0.0700***	-0.170*	-0.240**	-0.226***	-0.0668	-0.293**
	(-3.15)	(-1.80)	(-2.16)	(-3.52)	(-0.52)	(-1.99)
num_muse	-0.0145	-0.230	-0.245	-0.0312	0.0472	0.0161
	(-0.50)	(-1.36)	(-1.36)	(-0.80)	(0.32)	(0.10)
size_building	-0.0388	-0.252*	-0.291*	-0.125**	0.0839	-0.0412
	(-1.01)	(-1.87)	(-1.84)	(-2.04)	(0.49)	(-0.22)
Observation		496			496	
Log-likelihood		740.16			533.82	
Time fixed effect		No			Yes	
Wald test, spatial lag					24.88[0.003]	
Wald test, spatial					27.29[0.001]	
LR test, spatial lag					64.25[0.000]	
LR test, spatial					70.28[0.000]	

*p<0.10 **p<0.05 ***p<0.01

P=house average price (yuan), GDP=gross regional product (100 million yuan), CPI=consumer price index (preceding year=100), une_r=unemployment rate in urban area (%), pop_den=population density of urban area (person/sq.km), num_edu=number of regular institutions of higher education (unit), num_heal=number of health care institutions (unit), num_lib=number of institutions in public libraries(unit), num_muse=number of museums (unit), size_building=floor space of residential buildings completed (10000 sq.m), i and j=the location of house, t=time.

The indirect effect results across the different model specifications indicate that income flowing into a region is associated with a positive spill-over (indirect) effect on surrounding regions and that the effect appears to be larger relative to the direct effect. Prior to controlling for unobserved heterogeneities, house prices are found to increase by 46.1% with 1% increase in income in the surrounding regions. However, a 36.5% change in house prices based on a 1% change in income is observed when the investigation controls for time period fixed effects, as the investigation does in the spatial fixed model. In Table 6.4, the investigation applied the predicted house price in order to estimate the spatial model. Examining the spatial and time-period fixed effect results, the results provide that house prices are affected by variables of interest and surrounding factors significantly. The spatial fixed model is the first time applied and should capture the source of the parameter heterogeneity in the real options analysis. Regarding Van Dijk et al. (2011), neighbouring house prices should be a good approximation of the average house price development in the larger geographical region.

Overall, the results provide that house prices in a particular region are not only associated with factors in that region but also factors in surrounding regions. It implies that the indirect effects from surrounding regions are significant as well, specifically that larger indirect effects than direct effects are observed. These are interesting patterns that require further explanation. This result is similar to Mussa et al. (2017), who suggested that the indirect effects of variables in neighbouring regions have a greater explanatory weight than those in the target region. Thus, when the investigation considers house price uncertainty, it is suggested that surrounding effects of factors are also significant in China.

Table 6.4 Predict House Prices Estimation

$$P'_{it} = \alpha + \tau P_{it-1} + \rho \sum_{j=1}^{N} W_{ij} P_{it-1} + a_1 GPD_{it} + a_2 CPI_{it} + a_3 une\_r_{it} + a_4 pop\_den_{it} + a_5 num\_edu_{it} + a_6 num\_heal_{it} + a_7 num\_lib_{it} + a_8 num\_muse_{it} + a_9 size\_building_{it} + \theta_1 \sum_{j=1}^{N} W_{ij} GPD_{jt} + \theta_2 \sum_{j=1}^{N} W_{ij} CPI_{jt} + \theta_3 \sum_{j=1}^{N} W_{ij} une\_r_{jt} + \theta_4 \sum_{j=1}^{N} W_{ij} pop\_den_{jt} + \theta_5 \sum_{j=1}^{N} W_{ij} num\_edu_{jt} + \theta_6 \sum_{j=1}^{N} W_{ij} num\_heal_{jt} + \theta_7 \sum_{j=1}^{N} W_{ij} num\_lib_{jt} + \theta_8 \sum_{j=1}^{N} W_{ij} num\_muse_{jt} + \theta_9 \sum_{j=1}^{N} W_{ij} size\_building_{jt} + \nu_{it}$$

	Spatial fixed effect			Time-period fixed effect			Spatial and time-period fixed effect		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Rho(ρ)	0.606***			0.232			0.389***		
	(10.56)			(1.74)			(4.34)		
GDP	0.325***	0.408***	0.734***	0.480***	0.435***	0.916***	0.303***	0.222***	0.525***
	(12.86)	(11.08)	(16.58)	(5.65)	(2.66)	(4.93)	(10.96)	(2.81)	(5.81)
CPI	-1.043***	0.989***	-0.0538	-2.497***	-0.422	-2.919	-1.008***	0.950***	-0.0583
	(-8.07)	(4.68)	(-0.32)	(-2.93)	(-0.24)	(-1.59)	(-6.57)	(2.78)	(-0.15)
une_r	-0.135***	-0.561***	-0.696***	-0.494***	-0.536*	-1.030***	-0.137***	-0.457***	-0.595***
	(-4.57)	(-5.91)	(-5.88)	(-4.61)	(-1.84)	(-2.98)	(-5.74)	(-4.94)	(-5.32)
pop_den	-0.0171***	-0.00512	-0.0222	-0.0462*	-0.0423	-0.0885	-0.0238***	-0.0411**	-0.065***
	(-4.65)	(-0.32)	(-1.37)	(-1.70)	(-0.57)	(-1.16)	(-7.00)	(-2.50)	(-3.80)
num_edu	0.00906	0.297***	0.306***	0.0500	-0.788***	-0.738***	0.0270	0.311***	0.338***
	(0.53)	(3.98)	(3.93)	(0.45)	(-2.65)	(-2.72)	(1.30)	(4.74)	(4.32)
num_heal	-0.0112***	0.123***	0.112***	-0.162***	0.0693	-0.0927	-0.0140***	0.0720***	0.058***
	(-3.09)	(7.77)	(7.08)	(-3.82)	(0.42)	(-0.53)	(-4.05)	(5.81)	(4.71)
num_lib	-0.0458***	-0.110***	-0.155***	-0.237***	-0.120	-0.357**	-0.0408***	-0.0583**	-0.099***
	(-9.35)	(-3.40)	(-4.34)	(-3.56)	(-0.97)	(-2.33)	(-7.70)	(-2.06)	(-3.03)
num_muse	0.0149*	-0.249***	-0.234***	-0.0360	0.0270	-0.00901	0.0250***	-0.157***	-0.132***
	(1.88)	(-4.10)	(-3.61)	(-1.00)	(0.25)	(-0.07)	(3.55)	(-3.69)	(-2.86)
size_building	-0.0401***	-0.267***	-0.307***	-0.124**	0.0747	-0.0497	-0.0411***	-0.219***	-0.260***
	(-3.73)	(-5.43)	(-6.00)	(-2.52)	(0.50)	(-0.30)	(-4.17)	(-7.93)	(-9.55)
Observation		496			496			496	
Log-likelihood		1622.95			615.46			1666.34	
Time fixed effect		No			Yes			Yes	
Wald test, spatial lag		24.88[0.003]			43.55[0.056]			27.63[0.011]	
Wald test, spatial error		27.29[0.001]			69.87[0.065]			39.17[0.013]	
LR test, spatial lag		64.25[0.000]			52.19[0.071]			78.71[0.000]	
LR test, spatial error		70.28[0.000]			31.52[0.083]			55.32[0.000]	

*p<0.10 **p<0.05 ***p<0.01

P'=predict house average price (yuan), GDP=gross regional product (100 million yuan), CPI=consumer price index (preceding year=100), une_r=unemployment rate in urban area (%), pop_den=population density of urban area (person/sq.km), num_edu=number of regular institutions of higher education (unit), num_heal=number of health care institutions (unit), num_lib=number of institutions in public libraries(unit), num_muse=number of museums (unit), size_building=floor space of residential buildings completed (10000 sq.m), i and j=the location of house, t=time.

6.5.2 Implied Volatility

The future price uncertainty, σ_{it}^2, speculates that developers' confidence in their predicted price forecast depends on the availability of forecast prices in the recent past (Cunningham, 2006). The estimation of the variance of residuals suggests that the developers have additional information that influences the price. Thus, this investigation employs generalised autoregressive conditional heteroskedasticity (GARCH) to test future house price uncertainty, in which residuals from a forecasting equation (formula 6.5) are employed to measure volatility.

Table 6.5 House Prices Forecasting Parameter Estimates by Year

Mean equation:

$$P'_{it} = \alpha_i + \alpha_{1i}P'_{it-1} + \varepsilon_{it}$$

Variance equation:

$$\sigma_{it}^2 = a + \gamma\varepsilon_{it-1}^2 + \theta\sigma_{it-1}^2$$

Year	Intercept		Lagged 1-year price			
	Parameter estimate	Standard errors	Parameter estimate	Standard errors	LM-test	p-value
2000	3.464	(0.021)	-0.0002	(0.0001)	0.770	0.00
2001	3.458	(0.021)	0.0001	(0.0012)	0.657	0.01
2002	3.463	(0.018)	0.0007	(0.0007)	0.718	0.00
2003	3.481	(0.021)	0.0393	(0.0047)	0.774	0.00
2004	3.461	(0.020)	-0.0004	(0.0015)	0.637	0.00
2005	3.464	(0.018)	0.0002	(0.0001)	0.758	0.02
2006	3.424	(0.049)	0.0260	(0.0071)	0.888	0.00
2007	3.409	(0.015)	0.0190	(0.0204)	0.832	0.00
2008	3.417	(0.040)	0.0273	(0.0412)	0.991	0.00
2009	3.394	(0.014)	0.0488	(0.0206)	1.088	0.00
2010	3.365	(0.017)	0.0408	(0.0654)	1.033	0.00
2011	3.352	(0.025)	0.0279	(0.0301)	1.170	0.00
2012	3.368	(0.052)	0.0282	(0.0352)	1.212	0.00
2013	3.364	(0.023)	0.0237	(0.0021)	1.222	0.01
2014	3.388	(0.029)	0.0479	(0.0038)	1.110	0.00
2015	3.371	(0.062)	0.0321	(0.0497)	1.148	0.00

In Table 6.5, the investigation formally tests for autoregressive conditional heteroskedasticity (ARCH) effects employing a Lagrange Multiplier (LM) test and find evidence of ARMA effects. The investigation estimates the ARMA specification of (1) and collects the residuals. Subsequently, the model regresses the squared residuals on their own lags. If $n \times R^2$ from this regression exceeds a critical value, the null hypothesis of no ARCH effects can be rejected. Thus, the series can be seen to exhibit volatility clustering. Here, the results reject that the variance is constant. This result is in line with Wang et al. (2016), who found ARCH effects for house prices in Hangzhou housing market, China. It is also similar to the study of Cunningham (2006), who found ARCH effects for house prices in Seattle. It implices that the house price is influenced by not only fundamentals but also uncertainties. The GARCH method, which decreases the error term, provides that the price uncertainty, which is σ_{it}^2, rises when the analysis includes one-year-ahead house prices. This investigation calculates the option premium using the Black-Scholes model, in which the standard deviation of the stock's returns is required. The historical house price fluctuation has a predictable orientation to the future house price (Cunningham, 2006). Cunningham (2006) also suggested that "the current observed volatility of prices may be the best measure of future price uncertainty". Related to the studies of real options in China, Wang et al. (2016), Tang and Wang (2017) and Shi et al. (2015) are in line with the view of Cunningham (2006). Therefore, this investigation suggests applying the unconditional standard error of alternative regions in different years of China to represent the standard deviation of the stock's returns in the Black-Scholes model. The results of the unconditional standard error are displayed in Table 6.6.

Based on the above results, the investigation presents the standard error of house price in Table 6.6. The results found that the standard deviation of residential housing market in China ranges from 2.14% to 23.49%, depending on the time series of house prices. This result is in line with Wang et al. (2016), who provide a one-standard-deviation residential housing market in Hangzhou ranges from 13.39 % and 16.51 %. Case and Shiller (1989) provides an average of 15% standard deviation in individual house prices in alternative cities, such as Atlanta, Chicago, Dallas, and San Francisco-Oakland, from 1970 to 1986. Titman and Torous (1989) illustrate that there was a 15.5% standard deviation in property value employed by the model of commercial mortgage-pricing. However, Sheik and Vora (1990) argue that the different fundamentals could be altered by assuming constant variance to estimate implied variances. It implies that the volatility of underlying profits can be explored by implied volatilities reasonably, referred to as change variance.

Table 6.6 The Volatility of House Price

Mean equation:

$$P_{it} = \alpha_i + \alpha_{1i} P_{it-1} + \varepsilon_{it}$$

Variance equation:

$$\sigma_{it}^2 = a + \gamma \varepsilon_{it-1}^2 + \theta \sigma_{it-1}^2$$

Region	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Anhui	18.38%	18.85%	19.32%	13.75%	19.02%	19.16%	17.35%	18.04%	18.37%	13.77%	19.79%	20.07%	19.91%	18.77%	9.77%	18.12%
Beijing	22.12%	22.45%	23.49%	19.36%	22.83%	23.38%	18.04%	18.52%	19.29%	22.08%	20.96%	21.25%	21.35%	19.56%	21.86%	19.09%
Chongqing	8.01%	8.80%	7.49%	11.69%	9.13%	9.30%	5.03%	9.00%	4.97%	12.76%	4.75%	9.39%	17.30%	15.21%	12.37%	14.46%
Fujian	9.60%	10.50%	9.42%	13.88%	10.88%	11.46%	16.12%	13.77%	16.53%	16.80%	20.19%	16.71%	16.80%	15.38%	15.95%	17.93%
Gansu	9.92%	10.59%	9.56%	11.48%	10.71%	11.05%	16.68%	15.33%	17.25%	13.36%	19.10%	17.48%	17.70%	16.19%	12.76%	17.32%
Guangdong	11.54%	12.17%	11.43%	14.48%	12.51%	13.03%	17.77%	17.21%	18.73%	16.56%	20.68%	20.05%	20.21%	18.37%	15.91%	18.76%
Guangxi	7.78%	7.85%	6.00%	12.52%	7.32%	6.98%	15.06%	14.76%	15.96%	15.27%	17.28%	16.93%	17.45%	15.77%	14.50%	16.20%
Guizhou	9.32%	9.45%	7.72%	12.77%	8.63%	8.65%	17.59%	17.11%	18.66%	13.91%	20.79%	20.06%	20.39%	18.43%	13.06%	18.86%
Hainan	8.68%	9.58%	7.69%	13.02%	8.56%	8.97%	17.78%	17.80%	19.02%	15.89%	20.79%	20.95%	21.27%	19.17%	15.68%	18.91%
Hebei	5.69%	4.60%	3.01%	12.93%	5.63%	3.98%	16.77%	16.90%	17.97%	14.67%	19.10%	18.72%	19.04%	16.94%	14.08%	16.54%
Heilongjiang	6.76%	5.61%	4.48%	12.22%	6.25%	4.76%	17.93%	18.02%	19.18%	14.70%	20.92%	20.74%	20.99%	18.85%	13.74%	18.90%
Henan	7.56%	6.58%	5.82%	13.18%	7.04%	5.79%	18.17%	18.53%	19.52%	14.72%	21.03%	21.54%	21.74%	19.54%	14.28%	19.17%
Hubei	7.67%	6.74%	6.21%	12.23%	6.84%	5.93%	18.13%	18.64%	19.49%	14.77%	20.95%	21.73%	21.91%	19.70%	13.78%	19.09%
Hunan	9.19%	8.12%	7.97%	13.17%	8.06%	7.39%	18.19%	18.79%	19.60%	14.59%	21.03%	21.94%	22.16%	19.91%	14.12%	19.18%
Inner Mongolia	8.81%	8.28%	8.06%	12.46%	8.04%	7.62%	18.05%	18.69%	19.44%	15.01%	20.90%	21.85%	22.09%	19.77%	14.22%	18.97%
Jiangsu	9.60%	8.98%	8.14%	13.31%	8.14%	7.09%	17.60%	18.09%	18.64%	15.30%	19.75%	20.59%	21.18%	18.93%	14.48%	18.34%
Jiangxi	7.69%	7.59%	6.45%	12.54%	7.50%	6.80%	17.88%	18.40%	19.20%	14.00%	20.87%	21.40%	21.71%	19.48%	13.51%	18.95%
Jilin	9.24%	9.15%	8.20%	12.79%	8.76%	8.34%	18.14%	18.68%	19.51%	15.51%	21.06%	21.82%	22.09%	19.82%	14.55%	19.20%
Liaoning	9.65%	9.32%	9.13%	12.54%	9.62%	9.33%	17.93%	18.59%	19.28%	13.81%	20.73%	21.63%	21.98%	19.71%	13.30%	18.84%
Ningxia	9.18%	9.53%	9.27%	13.73%	10.15%	9.99%	17.92%	18.58%	19.24%	15.96%	20.88%	21.71%	21.88%	19.64%	15.29%	19.00%
Qinghai	10.59%	11.22%	11.35%	11.06%	11.96%	12.08%	18.09%	18.73%	19.30%	13.07%	20.99%	21.88%	22.10%	19.83%	11.88%	19.15%
Shaanxi	12.51%	13.15%	13.60%	14.84%	14.21%	14.42%	18.06%	18.73%	19.29%	16.88%	20.88%	21.86%	22.06%	19.84%	16.80%	19.09%
Shandong	15.10%	15.77%	16.67%	8.34%	17.07%	17.66%	18.19%	18.84%	19.56%	11.30%	21.05%	22.02%	22.26%	19.99%	17.98%	19.21%
Shanghai	18.34%	18.89%	20.34%	17.06%	20.54%	21.62%	18.16%	18.83%	19.59%	18.10%	21.02%	22.05%	22.31%	20.01%	19.64%	19.17%
Shanxi	8.87%	8.67%	7.51%	14.22%	8.42%	8.05%	7.79%	8.33%	8.09%	18.02%	7.26%	6.26%	4.82%	5.19%	16.04%	6.86%
Sichuan	10.10%	9.92%	9.07%	10.13%	9.61%	9.43%	16.47%	14.81%	16.97%	9.07%	20.18%	17.07%	16.98%	15.61%	10.42%	18.00%
Tianjin	12.20%	11.87%	11.21%	15.57%	11.46%	11.61%	17.87%	17.13%	18.91%	19.64%	21.00%	20.10%	20.20%	18.35%	17.93%	19.07%
Tibet	7.61%	8.53%	7.53%	9.35%	8.86%	8.64%	16.01%	15.79%	16.72%	8.92%	17.79%	17.62%	17.52%	15.79%	10.93%	15.59%
Xinjiang	9.13%	10.19%	9.46%	16.27%	10.55%	10.59%	17.77%	17.53%	18.65%	19.80%	20.79%	20.22%	19.99%	18.16%	17.68%	18.77%
Yunnan	10.88%	12.02%	11.62%	2.60%	12.56%	12.81%	17.97%	18.13%	19.21%	2.14%	20.81%	21.10%	21.06%	19.08%	5.74%	18.99%
Zhejiang	12.97%	14.22%	14.20%	19.59%	15.05%	15.71%	18.18%	18.57%	19.53%	21.96%	21.06%	21.70%	21.81%	19.65%	20.86%	19.17%

6.5.3 Uncertainty and Timing of Land Development

In Table 6.7, the investigation examines the effect of uncertainty on land development as a test for the presence of real options in land markets. To test the prediction, this research estimates the effect of house price uncertainty and future house prices on land value. The investigation specifies an proportional hazard model incorporating SDM model, using a data set where vacant land price is a transacted price. Based on the results, it is found that uncertainty delayed land development, as the coefficient of uncertainty was negative (-1.101). This result is similar to Cunningham (2006), who also suggested that uncertainty of house prices delays land development. The coefficient estimate for the price uncertainty term is both negative and significant, suggesting the presence of a real option premium. This result is in line with Tang and Wang (2017), who suggest the rising housing demand is accompanied by developers' strategic delay of land development in China. It provides the uncertainty of future information delay the land development in China based on land flexibility. These results support the theory, advanced by Titman (1985), that uncertainty about future house prices can decrease investment activity in the current period. Meanwhile, this context appropriately solves the agency problem based on investment timing (Jensen and Meckling, 1976). When the shareholder and agents capture the information of surroundings at the same time and plan the investment of options, the information asymmetric and timing of investment are solved in order to establish an optimal capital structure and maximise the shareholder's value. The results also provide the similar results to Wang et al. (2016), who found the uncertainty delay the land development by 42% in Hangzhou, China. In China, the central government policies, such as "freeze" in transactions, the purchase restrictions and increased land supplies, cannot be regarded as these measures have changed the fundamentals of the residential housing market, particularly with regards to damping the speculative fervour. This is because these policies curbed the house prices in short-term but did not correct the fundamental mismatch in the market between supply and demand or cool the enthusiasm of property speculators in the over-heated cities (Koss and Shi, 2018).

Table 6.7 The Effect of House Prices Uncertainty in Neighbouring Regions on Timing of Development and Land Prices

Timing of land development:

$$\delta Z = \tau Landprice_{it-1} + \rho \sum_{j=1}^{N} W_{ij} Landprice_{it-1} + a_1 fpriceh_{it} + a_2 uncer_{it} + a_3 GPD_{it} + a_4 CPI_{it} + a_5 une\_r_{it} + a_6 pop\_den_{it} + a_7 num\_edu_{it} + a_8 num\_heal_{it} + a_9 num\_lib_{it} + a_{10} num\_muse_{it} + a_{11} size\_building_{it} + \theta_1 \sum_{j=1}^{N} W_{ij} fpriceh_{jt} + \theta_2 \sum_{j=1}^{N} W_{ij} uncer_{jt} + \theta_3 \sum_{j=1}^{N} W_{ij} GPD_{jt} + \theta_4 \sum_{j=1}^{N} W_{ij} CPI_{jt} + \theta_5 \sum_{j=1}^{N} W_{ij} une\_r_{jt} + \theta_6 \sum_{j=1}^{N} W_{ij} pop\_den_{jt} + \theta_7 \sum_{j=1}^{N} W_{ij} num\_edu_{jt} + \theta_8 \sum_{j=1}^{N} W_{ij} num\_heal_{jt} + \theta_9 \sum_{j=1}^{N} W_{ij} num\_lib_{jt} + \theta_{10} \sum_{j=1}^{N} W_{ij} num\_muse_{jt} + \theta_{11} \sum_{j=1}^{N} W_{ij} size\_building_{jt} + \nu_{it}$$

Land prices:

$$Landprice_{it} = \alpha + a_1 fpriceh_{it} + a_2 uncer_{it} + a_3 GPD_{it} + a_4 CPI_{it} + a_5 une\_r_{it} + a_6 pop\_den_{it}$$

Explanatory variables	Timing of development		Land Prices
	Spatial		OLS
	land price	Wx	land price
fpriceh	2.984	1.428	0.576***
	(1.34)	(1.20)	(6.44)
uncer	-1.101***	0.176	1.829***
	(-3.78)	(0.27)	(5.21)
GDP	0.409	0.855	0.496***
	(-0.80)	(-0.90)	(16.10)
CPI	1.875	5.029*	1.601
	(-0.51)	(1.69)	(0.92)
une_r	-0.539**	-1.423**	-0.402***
	(2.06)	(1.98)	(-2.61)
pop_den	0.101	0.298	0.219***
	(1.44)	(1.40)	(4.48)
num_edu	-0.465	-1.574**	-
	(-1.42)	(-2.08)	
num_heal	-0.00546	0.360**	-
	(-0.09)	(2.00)	
num_lib	0.0264	-0.214	-
	(0.36)	(-0.63)	
num_muse	-0.264*	0.174	-
	(-1.87)	(0.51)	
size_building	0.0335	0.495	-
	(0.32)	(1.14)	
Observation	496		496
Log-likelihood	722.95		
Time fixed effect	Yes		Yes
Wald test, spatial lag	26.16[0.021]		
Wald test, spatial	29.82[0.016]		
LR test, spatial lag	58.37[0.000]		
LR test, spatial	64.58[0.000]		

*p<0.10 **p<0.05 ***p<0.01

Landprice=average land price (yuan), fpriceh=predict house average price (yuan), uncer=standard error of house price, GDP=gross regional product (100 million yuan), CPI=consumer price index (preceding year=100), une_r=unemployment rate in urban area (%), pop_den=population density of urban area (person/sq.km), num_edu=number of regular institutions of higher education (unit), num_heal=number of health care institutions (unit), num_lib=number of institutions in public libraries(unit), num_muse=number of museums (unit), size_building=floor space of residential buildings completed (10000 sq.m), i and j=the location of house, t=time.

6.5.4 Uncertainty and Land Prices

In the right-hand column of Table 6.7, the investigation regresses the price uncertainty on land prices to test the existence of real options in land markets. Price uncertainty increases the option premium on land so that the land becomes more valuable with uses other than urgent development. This investigation specifies an OLS model of vacant land prices, using a data set where vacant land prices are transacted prices. Based on the analyses, the results provide that the uncertainty affected land value by 1.82% significantly and positively. These results are in line with Tang and Wang (2017) and Shi et al. (2015), who suggest the uncertainty increases the land value. This result is also similar to Cunningham (2006), who suggested that uncertainty of house prices increases both land value and the real option premium. Through the results of 'Land Prices model', this research rejects the null hypothesis in favour of the presence of a real option premium, referred to as the coefficient estimate for the price uncertainty term is 1.82% above zero. Regarding the evaluation of land price, the increasing one-standard-deviation in price uncertainty raises the land price. If there is a greater level of price uncertainty according to the economic information, then the vacant land will be traded at a premium above discounted future rents in current low capital use, $R_{current}$.

6.5.5 Real Options Premium

Regarding Table 6.7, the increasing price uncertainty in the future raises the option premium. The result for the parameter estimates of price uncertainty is significantly above zero. This investigation could reject the null hypothesis that price uncertainty does not affect land values. According to the analysis of the impact of price uncertainty on the timing of land development and land value (Table 6.7), neighbouring house price uncertainty delays building activity and increases the land value. Thus, a real option exists in the land markets of China.

In Table 6.8, the investigation presents real option premium in all of the provinces of China. According to the method, this research provides the option premium, which is the difference between the option model price and the intrinsic value. The range of these option premiums is between 11.16% and 21.97%. The mean value of these option premiums is 16.28%. The results recognise that these option premiums are provided by a high bound for

Table 6.8 Summary Statistics of Option Premium

$$C = SN(d_1) - N(d_2)Ke^{-rt} \qquad d_1 = \frac{\ln\left(\frac{S}{K}\right) + \left(r + \frac{S^2}{2}\right)t}{s*\sqrt{t}} \qquad d_2 = d_1 - s*\sqrt{t}$$

Region	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Anhui	16.23%	18.10%	17.67%	18.73%	18.13%	17.73%	18.34%	15.00%	17.92%	17.18%	16.45%	16.69%	21.00%	12.71%	12.62%	13.85%
Beijing	16.89%	11.85%	17.58%	17.66%	18.76%	17.50%	19.03%	18.34%	15.32%	18.32%	17.13%	16.52%	19.78%	17.28%	12.42%	13.97%
Chongqing	17.34%	12.66%	12.51%	17.95%	16.57%	18.13%	18.77%	19.22%	17.74%	15.41%	18.19%	17.20%	16.56%	14.99%	17.14%	11.16%
Fujian	14.20%	12.61%	13.29%	11.77%	17.99%	16.94%	19.24%	18.96%	18.59%	18.36%	15.61%	18.22%	17.25%	15.78%	14.79%	18.04%
Gansu	20.37%	13.32%	13.22%	12.38%	12.06%	16.97%	17.02%	19.40%	18.50%	19.16%	18.27%	16.04%	18.35%	15.44%	15.57%	16.08%
Guangdong	18.67%	17.19%	13.24%	12.29%	12.93%	11.49%	18.13%	16.96%	18.97%	18.93%	19.11%	18.28%	16.60%	17.18%	15.87%	16.47%
Guangxi	16.19%	14.96%	17.53%	13.67%	12.66%	11.88%	11.74%	18.14%	17.10%	19.36%	18.83%	19.18%	18.34%	12.83%	17.08%	16.93%
Guizhou	16.88%	11.80%	15.48%	16.92%	13.88%	12.11%	12.09%	12.11%	17.76%	17.12%	19.28%	18.92%	19.27%	17.94%	12.78%	18.18%
Hainan	17.80%	13.21%	15.88%	14.47%	17.09%	13.54%	12.33%	12.50%	11.75%	18.15%	17.41%	19.37%	19.04%	17.00%	16.84%	11.79%
Hebei	14.65%	13.49%	15.67%	15.15%	14.87%	16.83%	13.55%	12.76%	12.31%	12.41%	18.05%	18.02%	19.44%	16.56%	17.24%	18.24%
Heilongjiang	17.76%	14.22%	17.31%	15.42%	16.39%	14.25%	16.88%	13.64%	12.37%	12.84%	12.77%	18.10%	19.23%	17.59%	16.80%	18.82%
Henan	18.35%	12.43%	14.48%	16.75%	16.78%	16.45%	14.33%	17.01%	13.68%	13.08%	13.53%	14.70%	18.13%	15.71%	17.66%	18.44%
Hubei	17.91%	14.02%	17.44%	15.30%	18.09%	16.88%	16.55%	14.58%	16.94%	13.68%	13.87%	15.46%	12.13%	17.61%	15.86%	19.04%
Hunan	18.91%	16.70%	17.17%	16.60%	15.58%	18.16%	17.16%	16.51%	14.44%	17.28%	13.07%	16.12%	12.62%	13.42%	16.56%	14.82%
Inner Mongolia	19.29%	17.43%	16.88%	16.93%	18.23%	15.05%	18.30%	17.18%	16.43%	14.97%	17.86%	12.08%	12.61%	13.79%	12.22%	18.05%
Jiangsu	17.66%	16.33%	17.82%	16.77%	18.75%	18.29%	15.08%	18.28%	17.05%	16.46%	15.82%	19.60%	14.41%	13.82%	13.14%	13.75%
Jiangxi	18.05%	16.10%	16.47%	17.66%	18.54%	18.66%	18.30%	15.19%	18.17%	17.14%	16.53%	18.03%	17.07%	15.02%	13.19%	14.78%
Jilin	18.61%	12.39%	17.31%	17.10%	19.08%	18.41%	19.12%	18.28%	14.75%	18.21%	17.21%	16.58%	14.66%	17.73%	15.34%	15.03%
Liaoning	19.34%	13.26%	13.15%	16.82%	17.57%	18.94%	18.85%	19.18%	18.27%	14.67%	18.22%	17.26%	12.36%	15.66%	17.49%	16.91%
Ningxia	16.80%	13.17%	13.91%	12.29%	18.02%	16.82%	19.31%	18.93%	18.97%	18.20%	14.35%	18.34%	13.01%	16.43%	15.33%	18.86%
Qinghai	21.97%	14.26%	13.90%	12.88%	11.26%	18.01%	16.83%	19.34%	18.75%	19.07%	18.33%	13.64%	13.97%	16.47%	16.38%	17.20%
Shaanxi	20.59%	17.57%	14.52%	12.67%	11.76%	11.71%	18.10%	17.00%	19.21%	18.88%	19.19%	18.35%	16.56%	18.04%	16.65%	16.57%
Shandong	16.51%	15.61%	18.02%	13.78%	12.07%	12.06%	12.24%	18.04%	16.73%	19.31%	18.94%	19.26%	12.83%	17.32%	17.93%	17.13%
Shanghai	17.11%	15.62%	16.16%	17.10%	13.85%	12.26%	12.45%	12.39%	18.03%	16.66%	19.36%	19.01%	13.29%	18.33%	17.40%	18.32%
Shanxi	18.21%	15.00%	16.38%	14.80%	16.80%	13.95%	12.73%	12.72%	12.26%	17.98%	16.16%	19.44%	12.57%	18.36%	18.23%	18.43%
Sichuan	18.49%	16.99%	16.50%	16.30%	14.23%	16.89%	13.95%	12.78%	12.78%	12.24%	18.13%	18.51%	14.85%	18.04%	18.42%	18.36%
Tianjin	18.31%	16.00%	17.96%	16.46%	15.92%	14.32%	17.01%	14.01%	12.80%	12.91%	13.56%	18.15%	17.71%	18.73%	17.94%	19.10%
Tibet	18.90%	17.95%	15.89%	17.93%	16.37%	16.57%	14.53%	17.03%	13.78%	13.13%	14.32%	16.22%	13.67%	18.50%	18.64%	18.80%
Xinjiang	18.58%	16.84%	18.18%	14.71%	17.62%	17.11%	16.58%	14.48%	17.12%	14.19%	14.77%	16.91%	12.58%	18.09%	18.39%	19.29%
Yunnan	19.25%	16.48%	18.34%	18.23%	15.04%	18.32%	17.23%	16.30%	14.72%	17.40%	14.69%	17.83%	13.05%	11.72%	17.95%	19.77%
Zhejiang	20.22%	17.50%	18.04%	18.35%	17.44%	15.06%	18.35%	16.91%	16.55%	15.15%	18.57%	15.71%	13.06%	12.58%	12.88%	18.13%

C=call premium, S=land value (sq.m), t=time until option exercise (2 years), K=predict house price (sq.m), r=risk-free interest rate (China 10 years bond yield), N=cumulative standard normal distribution, e=exponential term, s=standard deviation (house price volatility), ln=natural log.

land because the sample contains average land prices for all industries. Otherwise, there may be large standard errors although the variance estimates present the limited confidence intervals. These results are different from those of previous studies. Wang et al. (2016) found the real-option premium 9.76% in housing market in Hangzhou, China. Yao and Pretorius (2004) found the real-option premium 11.75% in housing market in Hongkong, China. Quigg (1993) found a real-option premium of 6% on undeveloped land that is relative to the deterministic price. Bulan et al. (2009) determined that a one-standard-deviation increase in conditional price volatility cause the prospect of development to be reduced by 13%. In this investigation, the results provided that the mean of land option premium is 16.28% in the average China's land market. There are some reasons for the high option premium in the Chinese land market. The real estate market in China is characterised as poorly liquid and decentralised (Tang and Wang, 2017). According to Shiller (1998), "illiquid (real asset) markets tend to be markets where the individual assets are idiosyncratic, having quality characteristics that are unique to each asset sold, assets that are difficult to describe or measure". The assessment of asset price could be a misunderstanding based on the inefficient financial market liquidity. Childs et al. (2001) point out that the decentralised trading is a feature of the real estate market. Continuous trading facilitates arbitrage by well-informed agents, bringing the prices of financial products to their fundamental prices. By contrast, decentralised trading in real estate markets inhibits arbitrage, generating difficulty in price discovery. Thus, the valuation of real estate typically contains plenty of information noises, especially in emerging markets like China (Hui et al., 2013). Childs et al. (2002) note that the phenomenon of phasing development observed in urban fringe or blighted urban land is an illustration of internalising the potential benefits of information spill-over arising from advanced investment. As the Chinese housing market has become overheated since the year 2003, the central government's control policies have become more and more intensive. Different from market-oriented policies in the developed economies, the Chinese government relies on the command-and-control approach, such as a limit on home-purchase and loan, censorship of real estate projects and so on. Those policies are notoriously inconsistent and short-run. Moreover, due to different objectives, sometimes the stance of the central government is quite different from that of the local government, which brings in more uncertainty to policies. Consequently, policy uncertainty in a transition economy like China could be very high.

Table 6.9 Regressions of Market Prices on Model Prices

The models are well specified if the coefficients are not significantly different from zero, and the constants are not significantly different from one. Option model:

$$land\ market\ price = a + b * option\ model\ price + \varepsilon$$

	Constant a	Std. Error	Coeff. b	Std. Error	R-square
2000	1.0577	0.0484	0.3901	0.0130	0.9679
2001	1.0457	0.0514	0.3888	0.0135	0.9653
2002	1.0827	0.0520	0.3784	0.0135	0.9634
2003	1.0074	0.0406	0.3970	0.0099	0.9816
2004	0.8819	0.0306	0.4045	0.0069	0.9914
2005	0.9938	0.0368	0.3927	0.0081	0.9873
2006	0.7548	0.0533	0.4431	0.0111	0.9814
2007	0.8016	0.0368	0.4308	0.0072	0.9917
2008	0.7537	0.0393	0.4343	0.0074	0.9915
2009	0.9648	0.0454	0.4071	0.0083	0.9876
2010	0.7696	0.0508	0.4315	0.0088	0.9876
2011	0.7623	0.0496	0.4307	0.0084	0.9886
2012	0.7718	0.0458	0.4300	0.0074	0.9912
2013	0.4302	0.0057	0.7546	0.0359	0.9948
2014	0.8770	0.0311	0.4166	0.0047	0.9962
2015	0.7893	0.0325	0.4291	0.0047	0.9964

The investigation establishes that several regressions in terms of the model are comparatively fitted. In Table 6.9, the research regresses the option value of land and market value of land. R-square suggests that the model processes reasonably. The investigation rejects the hypothesis that the coefficient (b) is one and the constant (a) is zero. This result is similar to Quigg (1993) who found that real options exist in the land market of the USA. According to Quigg (1993), when the constant is zero and the other coefficients are one, the option valuation model will be an appropriate depiction of land values. In this research, not only is the constant unequal to zero but also the option premium coefficients are positive and significant. Thus, the investigation has an approval that "option valuation model has some explanatory power for prices over and above the intrinsic value" (Quigg, 1993).

6.6 Conclusion

The weight of the evidence presented in this chapter suggests there are real options in China's real estate markets. Future price uncertainty drives up land prices in China. This finding is robust to a number of different parameterisations and a well-specified spatial regression on house price and vacant land. In the analysis of underlying house price, the test results justify the extension of the spatial model with spatial fixed effects and time period fixed effects and are similar to those of the previous study (Mussa et al., 2017), which tested the immigration effects on house prices in the USA. Thus, the results illustrate that neighbouring house prices affected house prices in this region, supporting the idea that house price has a ripple effect (Pijnenburg, 2017). In the Spatial Durbin Model (SDM) analysis of underlying house price, this study found an increase in income equivalent of 1% is associated with a 41.2% rise in house prices. This result is in line with Tang and Wang (2017), who suggest income increases the house price in China. The unemployment rate and CPI is negatively correlated with house prices. Similar empirical results were obtained by Harris et al. (2013) and Farlow (2004), who found that house prices were higher in cities with increased income and lower CPI and unemployment rates in China. The spatial fixed model is the first time applied and should capture the source of the parameter heterogeneity in the real options analysis. Regarding Van Dijk et al. (2011), neighbouring house prices should be a good approximation of the average house price development in the larger geographical region. The results of implied volatility analysis provide that house price in China has ARCH effects. This result is in line with Wang et al. (2016), who found ARCH effects for house prices in Hangzhou housing market, China. It is also similar to the study of Cunningham (2006), who found ARCH effects for house prices in Seattle. The standard deviation of residential housing market in China ranges from 2.14% to 23.49%, depending on the time series of house prices. This result is in line with Wang et al. (2016), who provide a one-standard-deviation residential housing market in Hangzhou ranges from 13.39 % and 16.51 %. Referred to the results of uncertainty and timing of land development, it is found that uncertainty delayed land development, as the coefficient of uncertainty was negative (-1.101). This result is in line with Tang and Wang (2017), who suggest the rising housing demand is accompanied by developers' strategic delay of land development in China. It provides the uncertainty of future information delay the land development in China based on land flexibility. The results also provide the similar results to Wang et al. (2016), who found the uncertainty delay the land development by 42% in Hangzhou, China. Based on the analyses, the results provide that the uncertainty affected land value by 1.82% significantly and positively. The unemployment rate influences the land value by 40.2%, significantly and negatively. These results are in line with Tang and Wang (2017) and Shi et al. (2015), who suggest the uncertainty increases the land value.

Market prices indicate a premium for optimal development of land, which according to our estimates has a mean of 16.28% of the land value. A one-standard-deviation increase in uncertainty reduces the likelihood of development by 1.101%. These results differ from those of previous studies. Wang et al. (2016) found the real-option premium 9.76% in housing market in Hangzhou, China. Yao and Pretorius (2004) found the real-option premium 11.75% in housing market in Hongkong, China. Quigg (1993) found a real-option premium of 6% on undeveloped land that is relative to the deterministic price. There are some reasons for the high option premium in the Chinese land market. The real estate market in China is characterised as poorly liquid and decentralised (Tang and Wang, 2017). According to Shiller (1998), "illiquid (real asset) markets tend to be markets where the individual assets are idiosyncratic, having quality characteristics that are unique to each asset sold, assets that are difficult to describe or measure". The assessment of asset price could be a misunderstanding based on the inefficient financial market liquidity. Childs et al. (2001) point out that the decentralised trading is a feature of the real estate market. Continuous trading facilitates arbitrage by well-informed agents, bringing the prices of financial products to their fundamental prices. By contrast, decentralised trading in real estate markets inhibits arbitrage, generating difficulty in price discovery. Thus, the valuation of real estate typically contains plenty of information noises, especially in emerging markets like China (Hui et al., 2013). Childs et al. (2002) note that the phenomenon of phasing development observed in urban fringe or blighted urban land is an illustration of internalising the potential benefits of information spill-over arising from advanced investment. As the Chinese housing market has become overheated since the year 2003, the central government's control policies have become more and more intensive. Different from market-oriented policies in the developed economies, the Chinese government relies on the command-and-control approach, such as a limit on home-purchase and loan, censorship of real estate projects and so on. Those policies are notoriously inconsistent and short-run. Moreover, due to different objectives, sometimes the stance of the central government is quite different from that of the local government, which brings in more uncertainty to policies. Consequently, policy uncertainty in a transition economy like China could be very high.

It is suggested that real options valuation has been undertaken to develop and improve the real assets investment valuation with investment flexibility, variability and irreversibility. Employing methods to account for uncertainty can increase the ability of decision making. Real options state the flexibility in decision making. Moreover, real options implement the flexibility to be inherently facilitated in irreversible investments. Whilst real options valuation has been applied to investment projects to account for the value of flexibility referred to the uncertainties where the traditional DCF is unable to do so.

It is recommended that the real option valuation is senior for real estate investment facing uncertain market which desires flexible and adaptive approaches. It is suggested that real options identify the uncertainties in real estate development, which is evident by development cost, the timing of building activity and incomplete information. While real options valuation is suggested to apply in the real estate market, the limitation and methodological guidance cannot be neglected. In this thesis, real options valuation is employed in the context of real estate investment to value the flexible options. The objective of this thesis is to extend a methodology with identified uncertainties for the application of real option in the Chinses housing market.

This context appropriately solves the agency problem based on investment timing (Jensen and Meckling, 1976). When the shareholder and agents capture the information of surroundings at the same time and plan the investment of options, the information asymmetric and timing of investment are solved in order to establish an optimal capital structure and maximise the shareholder's value. Regarding the evaluation of land price, the increasing one-standard-deviation in price uncertainty raises the land price. If there is a greater level of price uncertainty according to the economic information, then the vacant land will be traded at a premium above discounted future rents in current low capital use.

In the assumption of real options, the investment opportunity is directly managed by the principal, who also be the owner (McDonald and Siegel, 1986). Meanwhile, the agents are perfectly aligned with them (Dixit and Pindyck, 1994). Regarding the previous studies of agency conflicts with real options in the recent, Nishihara and Shibata (2008) extends the model involves the relationship between an audit mechanism and managers' behaviours with bonus-incentives. Shibata and Nishihara (2010) contributed the agency conflicts and real options based on debt financing on investment expenditure. Hori and Osano (2010) provided a model consider the managerial compensation that endogenously illustrated a contingent claim on firm's cash-flows using stock options. However, this investigation established a spatial method, which considered the effects of surrounding house prices and surrounding economic factors, has improved the accuracy of house price uncertainty estimation, in terms of reducing the agent problems of incomplete and asymmetric information. Thus, the optimal contract scheme could be proposed by real options approach with spatial analysis. In this context, this investigation avoids inadequate information from the agent in order to encourage the shareholders to follow the future evolution of investment value so that to achieve the optimal profits.

Although previous studies, such as Titaman (1985), Quigg (1993), Cunningham (2006), applied the OLS specification to examine house price uncertainty, the investigation established a spatial method which also considered the effects of surrounding house prices and surrounding economic factors in order to improve the accuracy of house price uncertainty estimation. Accordingly, this research extended this model by incorporating a spatial Durbin model. Our evidence links spatial analysis and GARCH analysis, which adds to our overall understanding of house price uncertainty.

The results of this study suggest that investors in China's real estate do take note of real options, even in sectors such as new home construction that is highly competitive and economically important. That real options are present in land markets is further evidence for the need to include real options in capital investment models. Real options have wider implications concerning the importance of price stability and the need for consistent government policy to stimulate fixed investment.

Chapter 7 Conclusion

7.1 Overview

This thesis has investigated several important issues relating to real estate markets in China. Chapter 4 investigated the influences of house characteristic and economic fundamentals on house prices of Beijing and introduced new flat-related factors that influencing house price. Moreover, this investigation employed IV-GMM method to explore the endogeneity of the variables with instrumental variables. Chapter 5 investigated the spatial statistics of house prices in Beijing and examined whether the house prices in one region are affected by the house prices in neighbouring regions. This investigation also analysed how the house prices in one region are affected by unknown characteristics of the neighbouring regions. Moreover, it explored whether the explanatory factors of house prices in one region are affected by explanatory factors of house prices in neighbouring regions. Subsequently, the objective was to investigate the spatial spill-over effects of explanatory factors. Chapter 6 investigated the real options for the spatial analysis in China's real estate markets and extended the real options method with spatial Durbin model (SDM), making this the first time that real option predictions have been tested in a spatial manner. Chapter 6 also measured the degree of price uncertainty by a generalised autoregressive conditional heteroskedasticity (GARCH) model. The weight of the evidence suggested there are real options in China's real estate markets. Uncertainty about future house prices of neighbouring regions drives up land prices in China. The objective of this thesis has been to extend the existing literature and provide potential explanations for the contradictory results reported in the existing literature, thus contributing to the empirical foundations in the real estate area.

7.2 Summary of Key Findings and Implications

Chapter 4 explored the empirical relationship among property prices, economic fundamental effects and property characteristics effects via the panel model and IV-GMM estimation. This chapter overcomes the omitted variables of house characteristics, leading to biased estimates of the implicit house price, compared with the previous studies (Rosen, 1974; Bajari et al., 2010). The house characteristics have influenced the property price significantly, which indicates that consumer behaviour is an essential aspect of the housing market (Rosen, 1979). The results have rejected the hypotheses that economic fundamentals and house characteristics are exogenous variables on property price. Therefore, this study provides innovative evidence that the economic fundamentals and the house characteristics are essential factors in the Chinese housing market. This result is supported by a number of previous studies in western country (Jim and Chen, 2009; Larraz and Alfaro, 2008; Malpezzi, 2002; Meen, 1996; Oikarinen, 2006; Rosen, 1974) and in China (Gan et al., 2012; Horioka and Wan, 2007; Hui and Gu, 2009; Li and Chand, 2013; Li et al., 2018; Shen and Liu, 2004; Taylor, 2000; Wong et al., 2005; Yu, 2010; Zhang and Yi, 2017).

Regarding the house characteristics, house size is leading to an increase in house prices which is in line with Zhang and Yi (2017) who found there is a positive relationship between house price and size of living area in Beijing. This result is also similar to Fang et al. (2016) who provide that despite the critical financial burdens afforded by the households, the home size is spacious which is more than the standards of most metropolitan areas in the world. It implies that home size in Beijing influences the housing demand in terms of China's characterised consumer behaviour of households who prefer to buy larger-size house. There is a significant positive relationship between house prices by floor level and negative relationship on property prices with FR^2. This result is similar to a previous study by Wong et al. (2005). This means the floor level influences the house price positively from the lower floor level to the middle floor level in a tall building. However, from the middle floor level to the upper floor level, the floor level influences house prices negatively. It implies that the household in Beijing preferred to buy a similar condition house with the lower price. The number of bedrooms has a significant negative influence on property prices. This situation may be based on privacy. According to Fahey (2016), one-bedroom rents are more expensive than two-bedroom rents. In terms of the house orientation, the north and south factor is significant and positive, which means that houses facing north and south have an increased price of 2.48%. This result is found in the previous studies (Fang et al., 2016 and Zhang and Yi, 2017). This is because houses facing north and south have better natural ventilation and more daylight, which improves the natural quality of a house and its energy efficiency. However, it is similar to Jim and Chen (2009) who suggested that daylight and views from houses are significant factors affecting house price.

Regarding the economic fundamentals, the mortgage down payment has a significant negative influence on property prices. This result is in line with Fang et al. (2016), Yu (2010) and Li and Chand (2013), who provided the mortgage down payment influence China's urban house prices negatively by data between 1998 and 2009. Thus, it is suggested that the high levels of down payments in China should be kept which can not only reduce the risk of household default for the bank but also decline the housing demand significantly. The average income of citizens influences house price significantly and positively. This result is in line with Hui and Gu (2009) and Shen and Liu (2004), who provide income significantly influence the house price in China. Housing assets have been a significant part of household wealth in China. The housing assets accounted for 66% of household wealth in China in 2016 (Liu and Xiong, 2018). Therefore, it is recommended that the demand for purchasing power in the Chinese housing market is influenced by the household incomes. The demand quantity of properties (Floor*House_permissions) has an inverse U-shape relationship with house prices. This result is not similar to Li et al. (2018), who provide the ratios of residential floor space under construction to floor space increase house price each year after 2004. This is because the thesis improved the method of calculating house demand, which is more flexible with an inverse U-shape relationship to explore the house price and house demand. Although some studies were undertaken in different countries, all of the results corresponded with economic theory. Based on such findings, economic factors have a significant influence on property prices in Beijing.

Baltagi (2001) provides that employing the values of the other variable regressors as instruments can increase consistency and efficiency of the model. The IV-GMM model employed the instrumental variables to improve the efficiency of the model. Meanwhile, the IV-GMM method restricted unobserved heterogeneity and limited the consistency of the dependent variable. To deal with this, the independent variables employed in this investigation refer to the IV-GMM method. The result provides that the central bank interest rates (IR) significantly influence the income (IC) positively and the inflation (CPI) influences the income (IC) negatively and significantly. This result confirms that of Horioka and Wan (2007), who found the real interest rate has a significant positive impact on the household income in China between 1995 and 2004. It implies that the central bank interest rates and inflation influences the house price in Beijing indirectly which is in line with Koss and Shi (2018).

Regarding the fiscal factors which are treated as the instruments to the variable of mortgage down payments, the results provide that the investment in fixed assets (IFA) affect the mortgage payment rates positively and significantly. If the local government general budgetary revenue (GR) increases, the mortgage payment rates will be increased significantly. The mortgage payment rates will be increased significantly when the local government general budgetary expenditure (GE) increases. Based on these results, IFA and GE influence mortgage payment rates positively, which is in line with the theory of 'conventional wisdom' (Galbraith, 1958). The results also are in line with Taylor (2000), who provide the instruments of fiscal policy change aggregate demand and influence the monetary policy indirectly in China. However, the result, which money supply (MS) and GR influence mortgage payment rates positively, is contrary to the 'conventional wisdom' (Galbraith, 1958) and the 'quantity theory of money' (Irving, 1911). The reason for that may be referred to the Budget Law. The local governments expend the fiscal capacity by non-budgetary funding sources such as land sales (Liu and Xiong, 2018). Therefore, the increasing government revenue cannot restrain the demand for investments in the housing market. Regarding China's "Local Government Financing Platform" (LGFP), the increase of government revenue means upward pressure on mortgage payment rates. Though the money supply increases, the aggregate demand for GDP is increasing rapidly so that exceed the amount of money supply, caused the increase of interest rate. Therefore, when the central government tightens monetary policy to limit debt accumulation by local governments, LGFP has been regulated. Accordingly, the fiscal factors and interest rate influence the house prices in Beijing indirectly.

Furthermore, the results provide the house orientation (Orien) influences the condition of the bedroom and the condition of living room positively and significantly. The orientation factors of SE NW WE and SW negatively influence the number of bedrooms respectively and significantly. The orientation factor of W negatively influences the number of the living rooms significantly. The orientation factor of WE affects the number of living rooms positively and significantly. The results of this study are in line with Jim and Chen (2009), who suggested that daylight and views from houses are significant factors affecting house prices. After adding the instrumental variables (orientation factors) in different models, the investigation found that the coefficients of BR are decreased. The coefficient of LR is increased. These results are in line with Rosen (1974). However, when the investigation considers the factor of floor level with number of bedrooms, the factor of Bedroom*Floor influences house prices positively and significantly with instruments of SE SW and SW NW respectively. The coefficient of Living_room*Floor increases. This means the more bedrooms are facing southeast and southwest or facing southwest and northwest with higher floor level, the higher house price. The more living rooms are facing west or east with higher floor level, the higher house price. Generally, the house facing south and west have more extended daylight, which increases the temperature of the room, so that increase the electrical efficiency. However, the bedrooms facing southwest, southeast or northwest not only keeps daylight but also reduces west sunburn and improves natural ventilation to improve sleeping context. The living room improves west sunburn increasing the whole house temperature so that increase house efficiency. Moreover, the higher floor level of houses, the more efficient daylight and natural ventilation. Thus, this investigation found the more numbers of rooms with proper orientation, the better condition of the room is which has good daylight and better natural ventilation. This result provides the orientation of the property influence the property prices indirectly in Beijing.

Regarding IV-GMM methods, the hypotheses are examined by the endogenous test. In the hypotheses, the coefficients of the independent variables are not significant and are individually equal to zero. If the null hypothesis is not rejected, the model is not efficient so that to modify the equation. With regards to the efficient model, the null hypothesis should be rejected so that the independent variables are significant in the general regression. Alternatively, the investigation could reduce the number of non-significant variables to estimate a confining hypothesis. Such estimations yield consistent estimations of the parameters. The coefficients of independent variables are respectable and refer to the restriction for the number of independent variables. According to the test of error terms unrelated to regressors, the hypothesis is rejected, which means that the regressors have endogeneity. With respect to linear instrumental variables regression, this investigation applies and tests the instrumental variables and endogeneity in order to establish IV-GMM models. As there is heteroscedasticity in the model, the GMM model is more efficient than the 2SLS model. This research employs mortgage payment rates, income, house planning permissions, number of bedrooms, number of living room as the endogenous variable respectively. The results of test reject the null hypothesis, indicating that IV-GMM is efficient and appropriate to be employed in the investigation of house prices in Beijing in terms of the relevant factors influencing the house prices indirectly.

In conclusion, this investigation complements the literature that studies the determinants of real estate markets and the economic area. This research is based on the panel model and IV-GMM, which could monitor the process of influencing factors. Defining the endogenous variable through instrumental variables is more detailed in terms of analysing exogenous variables. This investigation factors in a new variable of the orientation of property. This variable has never been analysed in previous studies. Through the panel analysis and GMM model, the results found that the orientation of property has influences on property price directly and indirectly. In addition, this study examines an extended period (2002-2014), which provides a sample of 17,143 property transaction records containing detailed information to examine the whole of Beijing's core real estate area. It encourages the developer of houses to have a rational house structure in order to have a maximum shareholder value. It also implicates that the regulators of banks and government should monitor the mortgage payment rate, interest rate, government revenue and expenditure in order to deter the irrational increasing house price.

Chapter 5 analyses the spatial statistics of house prices in Beijing, China with the spatial autoregressive model (SAR), spatial Durbin model (SDM), a spatial autoregressive model with autoregressive disturbances (SAC) and spatial error model (SEM). The analyses of spatial characteristics in house price dynamics with spatial dependence, spatial heterogeneity and spill-over effects of explanatory are estimated. While spatial dependence and spatial heterogeneity are well-established aspects of house price developments, spatial partitioning has not gained much attention yet. The investigation confirms that the disposition effect might explain different house price spill-overs across space. On the aspect of analysing direct and indirect (spill-over) effects, Chapter 5 examines the partitioning of direct and indirect effects and finds out the impacts of the neighbouring characteristics from a close distance (immediate neighbours) to the faraway distance on property prices.

The results of Chapter 5 reveal strong house price spill-overs when the increase in house price, size of building started, average wage, income, tax, and a population of the neighbouring regions is taken into account. The evidence for the disposition effect is based on the below results. The house price spill-overs in Beijing area exist when there is an increase in the population of the neighbouring regions, significant upper house price spill-overs are detected in terms of increasing house prices in the neighbouring regions. This result is similar to Zhang et al. (2015) and Chow et al. (2016), which means the urban population influence house prices positively and significantly in Beijing. This finding is in line with Alonso (1964), who provides the population is a significant factor in the economic analysis, because the population changes the demand for the number of houses. In the theory of 'the concentric zone' (Burgess, 1925), the development of ideal construction of the city expands from its CBD. The workers live near CBD aims to easy access to their work. Thus, the demand for house surrounding CBD is high, which causes the increase in house price. The findings of this analysis are also in line with Burgess's theory (1925) that the distance from district to CBD influenced the house price significantly and negatively. This encourages the regulators of Beijing housing market to establish the rational distribution of fixed assets effectively deter the unstable house price variation referred to the population changes. The differences in household income cause changes in residential location and house prices based on the ‘sector theory’ (Hoyt, 1939). This result is in line with Shen and Liu (2004). The income significantly influences the house price in Beijing and changes the distribution of house prices. This investigation provides a similar result to Hoyt’s theory (1939), which the average wage of employees in the real estate market leads to an increase in house price. This finding is also in line with the theory of ‘the concentric zone’ (Burgess, 1925), which presents the high-income group ‘who have escaped from the area of deterioration’ changes the demand of residential location. This encourages the regulators of Beijing housing market to establish the subsidiary CBD in Beijing in order to arrange rational distribution of fixed assets. Evans (1973) found that there is an equilibrium relationship between the density and revenue of houses in ‘the theory of the supply of space’. Thus, even though there is enough space for construction, the irrational density of buildings leads to lower revenues of the house. Size of building starts, which instead of the supply of houses, influences house prices positively. This result is in line with Hanink et al. (2012) and Zhang et al. (2018) who provide house starts is a potential determination of new construction rate which reflects the supply of housing market in Beijing. However, the result is not very significant. The result is similar to Evans (1973), who suggests a rational space and density of constructions are significant to households. Thus, it encourages the regulators of Beijing housing market to control the building permits and continue updating the policy of construction so that rationally monitor the supply of houses. The research found the taxes and other charges on principal business of enterprises for real estate development lead to an increase in house price significantly. This result is similar to the previous studies (Li and Chand, 2013; Liu, 2013), which means the taxes and other charges on principal business of enterprises for real estate development influence house prices negatively and significantly in Beijing. Based on the trade-off theory (Evans, 1973), the maximum utility of the household is the objective of the choice of location. The increasing tax added the costs of construction, and then the developers will increase the house selling price so that balance the costs. When the household considers the house price, they will change the location of living so that the patterns of residential location changes. Thus, it encourages the regulators of Beijing housing market to control the tax rates, so that have a rational distribution of constructions.The results of partitioning analyses are appropriately explaining the effects of surroundings, which can approach the utilities.

Because of loss aversion, homeowners who intend to sell their properties will not lower their asking price, even when they see house prices declining in neighbouring regions. Loss aversion reduces the number of transactions in the housing market and, reduces the amount of house price spill-over. Results of this study are similar to previous findings (Genesove and Mayer, 2001; Engelhardt, 2003; Anenberg, 2011) with regards to loss aversion in the housing market. This result is also in line with the previous studies (Yang, Noah, and Shoff, 2015), who show that the results of significant levels of the partitioned indirect effects in the second order are higher than those of the other order neighbours, which are referred to in the complicated estimation process in Spatial Durbin Model. Thus, it is suggested that the regulators of Beijing housing market should monitor the economic factors and population in the different order regions in order to adjust the house prices.

Chapter 5 extends previous research in terms of the data sample and independent variables used, and by combining methods used in economics and geography. In particular, this investigation examines 15 regions of Beijing over an extended period (2002-2014). It contains detailed information, building on and extending the work of Bhattacharjee et al. (2016), who analysed spatial heterogeneity and endogenous spatial dependence in Portugal. Regional house price records are linked with the coordinates of regions to track the spatial heterogeneity of house prices, and the region-related factors are employed in Beijing. Most of the previous empirical studies that combined geographic factors focused on the area of environment, health outcome, crimes and policy analyses (Hund et al., 2015; Neelon and Gelfand, 2014; Seliske et al., 2016; Terán-Hernández et al., 2016). These factors can be extended by our method with spatial partitioning, which can analyse the intensity of spill-over effects of explanatory factors. Chapter 5 presents the evidence for the spatial dependence of house prices: house prices in one region are influenced by the house prices in neighbouring regions positively and significantly. The evidence is found for spatial heterogeneity of house prices across space: house prices in neighbouring regions spill-over more in times of increasing neighbouring house prices than when neighbouring house prices are declining. The evidence is found for spatial spill-over effects of explanatory factors: increases of the average wage, income, tax, urban population and house price of the previous year increase the house price positively in neighbouring regions; a decrease of unemployment drives down the house prices in neighbouring regions. These factors have spill-over effects across space.

Chapter 6 provides the evidence that there are real options in China's real estate markets. Uncertainty about future prices drives up land prices in China. This finding is robust to various parameterisations and a well-specified spatial regression on house price and vacant land. In the analysis of underlying house price, the test results justify the extension of the spatial model with spatial fixed effects and time period fixed effects and are similar to those of the previous study (Mussa et al., 2017), which tested the immigration effects on house prices in the USA. Thus, the results illustrate that neighbouring house prices affected house prices in this region, supporting the idea that house price has a ripple effect (Pijnenburg, 2017). In the Spatial Durbin Model (SDM) analysis of underlying house price, this study found an increase in income equivalent of 1% is associated with a 41.2% rise in house prices. This result is in line with Tang and Wang (2017), who suggest income increases the house price in China. The unemployment rate and CPI is negatively correlated with house prices. Similar empirical results were obtained by Harris et al. (2013) and Farlow (2004), who found that house prices were higher in cities with increased income and lower CPI and unemployment rates in China. The spatial fixed model is the first time applied and should capture the source of the parameter heterogeneity in the real options analysis. Regarding van Dijk et al. (2011), neighbouring house prices should be a good approximation of the average house price development in the larger geographical region. The results of implied volatility analysis provide that house price in China has ARCH effects. This result is in line with Wang et al. (2016), who found ARCH effects for house prices in Hangzhou housing market, China. It is also similar to the study of Cunningham (2006), who found ARCH effects for house prices in Seattle. The standard deviation of residential housing market in China ranges from 2.14% to 23.49%, depending on the time series of house prices. This result is in line with Wang et al. (2016), who provide a one-standard-deviation residential housing market in Hangzhou ranges from 13.39 % and 16.51 %. Referred to the results of uncertainty and timing of land development, it is found that uncertainty delayed land development, as the coefficient of uncertainty was negative (-1.101). This result is in line with Tang and Wang (2017), who suggest the rising housing demand is accompanied by developers' strategic delay of land development in China. It provides the uncertainty of future information delay the land development in China based on land flexibility. The results also provide the similar results to Wang et al. (2016), who found the uncertainty delay the land development by 42% in Hangzhou, China. Based on the analyses, the results provide that the uncertainty affected land value by 1.82% significantly and positively. The unemployment rate influences the land value by 40.2%, significantly and negatively. These results are in line with Tang and Wang (2017) and Shi et al. (2015), who suggest the uncertainty increases the land value.

Chapter 6 denotes that the market prices indicate a premium for optimal development of land, which according to our estimates has a mean of 16.28% of the land value. A one-standard-deviation increase in uncertainty reduces the likelihood of development by 1.101%. These results differ from those of previous studies. Wang et al. (2016) found the real-option premium 9.76% in housing market in Hangzhou, China. Yao and Pretorius (2004) found the real-option premium 11.75% in housing market in Hongkong, China. Quigg (1993) found a real-option premium of 6% on undeveloped land that is relative to the deterministic price. There are some reasons for the high option premium in the Chinese land market. The real estate market in China is characterised as poorly liquid and decentralised (Tang and Wang, 2017). According to Shiller (1998), "illiquid (real asset) markets tend to be markets where the individual assets are idiosyncratic, having quality characteristics that are unique to each asset sold, assets that are difficult to describe or measure". The assessment of asset price could be a misunderstanding based on the inefficient financial market liquidity. Childs et al. (2001) point out that the decentralised trading is a feature of the real estate market. Continuous trading facilitates arbitrage by well-informed agents, bringing the prices of financial products to their fundamental prices. By contrast, decentralised trading in real estate markets inhibits arbitrage, generating difficulty in price discovery. Thus, the valuation of real estate typically contains plenty of information noises, especially in emerging markets like China (Hui et al., 2013). Childs et al. (2002) note that the phenomenon of phasing development observed in urban fringe or blighted urban land is an illustration of internalising the potential benefits of information spill-over arising from advanced investment. As the Chinese housing market has become overheated since the year 2003, the central government's control policies have become more and more intensive. Different from market-oriented policies in the developed economies, the Chinese government relies on the command-and-control approach, such as a limit on home-purchase and loan, censorship of real estate projects and so on. Those policies are notoriously inconsistent and short-run. Moreover, due to different objectives, sometimes the stance of the central government is quite different from that of the local government, which brings in more uncertainty to policies. Consequently, policy uncertainty in a transition economy like China could be very high.

In Chapter 6, most research in this area has focused on the house price uncertainty in a panel dataset. This approach provides a basis for testing the main expectations of real options with regard to land development: namely, that neighbouring house price uncertainty should delay building activities and increase the value of vacant land. Although previous studies, such as Titaman (1985), Quigg (1993), Cunningham (2006), applied the OLS specification to examine house price uncertainty. This investigation extends the real options method with the spatial Durbin model (SDM), making this the first study in which real option forecast have been assessed in a spatial case. The evidence of this research links spatial analysis and GARCH analysis, which adds to the overall understanding of house price uncertainty. This investigation overcomes the prior studies by extended sample with three datasets have been assembled for this investigation: house price files, land price files and GIS files for each location. When they are combined, these records produce a data set of 496 average house prices and average land prices in 31 provinces of China, for the period 2000 to 2015.

It is suggested that real options valuation has been undertaken to develop and improve the real assets investment valuation with investment flexibility, variability and irreversibility. Employing methods to account for uncertainty can increase the ability of decision making. Real options state the flexibility in decision making. Moreover, real options implement the flexibility to be inherently facilitated in irreversible investments. Whilst real options valuation has been applied to investment projects to account for the value of flexibility referred to the uncertainties where the traditional DCF is unable to do so.

Rather than extracting expectations from subsequently reported advantages, Chapter 6 uses the Black-Scholes' (1973) pricing model to explore the option premium of land value, which concerns current stock price, time until option exercise, option striking price, risk-free interest rates and standard deviation. For the conception of real options, the analyses considered market land value as current stock price, future house price as option striking price, and house price volatility as standard deviation (Quigg, 1993) in order to determine the land option premium.

It is recommended that the real option valuation is senior for real estate investment facing uncertain market which desires flexible and adaptive approaches. It is suggested that real options identify the uncertainties in real estate development, which is evident by development cost, the timing of building activity and incomplete information. While real options valuation is suggested to apply in the real estate market, the limitation and methodological guidance cannot be neglected. In this thesis, real options valuation is employed in the context of real estate investment to value the flexible options. The objective of this thesis is to extend a methodology with identified uncertainties for the application of real option in the Chinses housing market.

This context appropriately solves the agency problem based on investment timing (Jensen and Meckling, 1976). When the shareholder and agents capture the information of surroundings at the same time and plan the investment of options, the information asymmetric and timing of investment are solved in order to establish an optimal capital structure and maximise the shareholder's value. Regarding the evaluation of land price, the increasing one-standard-deviation in price uncertainty raises the land price. If there is a greater level of price uncertainty according to the economic information, then the vacant land will be traded at a premium above discounted future rents in current low capital use.

In the assumption of real options, the investment opportunity is directly managed by the principal, who also be the owner (McDonald and Siegel, 1986). Meanwhile, the agents are perfectly aligned with them (Dixit and Pindyck, 1994). Regarding the previous studies of agency conflicts with real options in the recent, Nishihara and Shibata (2008) extends the model involves the relationship between an audit mechanism and managers' behaviours with bonus-incentives. Shibata and Nishihara (2010) contributed the agency conflicts and real options based on debt financing on investment expenditure. Hori and Osano (2010) provided a model consider the managerial compensation that endogenously illustrated a contingent claim on firm's cash-flows using stock options. However, this investigation established a spatial method, which considered the effects of surrounding house prices and surrounding economic factors, has improved the accuracy of house price uncertainty estimation, in terms of reducing the agent problems of incomplete and asymmetric information. Thus, the optimal contract scheme could be proposed by real options approach with spatial analysis. In this context, this investigation avoids inadequate information from the agent in order to encourage the shareholders to follow the future evolution of investment value so that to achieve the optimal profits.

Although previous studies, such as Titaman (1985), Quigg (1993), Cunningham (2006), applied the OLS specification to examine house price uncertainty, the investigation established a spatial method which also considered the effects of surrounding house prices and surrounding economic factors in order to improve the accuracy of house price uncertainty estimation. Accordingly, this research extended this model by incorporating a spatial Durbin model. Our evidence links spatial analysis and GARCH analysis, which adds to our overall understanding of house price uncertainty.

The results of this study suggest that investors in China's real estate do take note of real options, even in sectors such as new home construction that is highly competitive and economically important. That real options are present in land markets is further evidence for the need to include real options in capital investment models. Real options have wider implications concerning the importance of price stability and the need for consistent government policy to stimulate fixed investment.

7.3 Future Research

This PhD thesis set out to construct an appropriate composite model and real estate market condition for the unique characteristics of valid evidence and trust modelling, based on the data employed. Such research is, to the best of my knowledge, original and sufficient at PhD level with various potentially significant contributions to both academic and practical applications. The composite measure of real estate, if successfully designed and proven to be reliable, will attract great attention from practitioners. Moreover, the fundamental analysis models developed for land and house prices will also be of significant interest to practitioners since they can enhance their operational methods. All of the topics addressed in this PhD thesis are relevant to current discussions taking place in academic literature, making the new knowledge presented here an important contribution to the growing body of literature on economic research and real estate valuation in China. For investors, this research could guide future real estate investment. However, there are limitations, which suggest avenues for future research.

In the investigation of determinants of house prices in seven districts of Beijing (Chapter 4), the results of the dominance of the panel models were obtained for only a selection of cities in the north of China. Further research is suggested to determine whether our results are specific to the particular dataset or the specification of the IV-GMM model. For instance, this investigation provides that floor level influences house prices positively, from the lower floor level to the middle floor level in a tall building; however, above the middle floor level, floor level influences house prices negatively. Meanwhile, when the research controls the floor level, the results provide that bedrooms facing southwest and southeast increase house prices significantly. Nonetheless, whether the same situation occurs in southern China is worth consideration. In the south of China, weather and geographical conditions are different from those in the north. Thus, the natural ventilation and the amount of daylight a house receives are also different. For future research, it would be worth investigating whether the house characteristics examined in this study also influence house prices in the south of China.

Regarding the development of the real estate market in China, the government's "217th policy", introduced in 2001, made changes to the various structures of the housing market from land supply, house construction, and market consolidation and regulations. The market response to this policy was to slow the rate at which house prices increased. However, Beijing house prices continued to rise. While this study investigates the influence of house characteristics on house prices, further research could analyse the degree to which prices have been affected by house construction regulations. Moreover, whether or not this policy affected particular regions, such as Beijing, it is worth further analysis in future studies. For instance, in the history of China's housing market, the Capital Planning and Construction Commission Office of Beijing enacted "Beijing Regulatory Detailed Planning (BRDP)". BRDP drew from the experience of American "zoning laws" to regulate details about construction projects and the city's overall planning. Table 7.1 provides the details of classification of residential building height. Whether these policies influence house prices are not yet known. Further work along these lines is called for, to check the other instrumental variables of house characteristics in the particular period.

Table 7.7.1 Classification of Residential Building Height

	Requirement	Range of Building Height
I	Building height is smaller than 18m	<18m
II	Building with 9 floor levels or below 9 floor levels	≥ 18m and <30m
III	Building with floor level between 10 and 18	≥ 30m and <60m
IV	Building with floor level above 18 floor levels	≥ 60m and <100m
V	Super high floor level building	≥ 100m and ≤250m

m is meter

In Chapter 4, the results provide that the number of bedrooms has a significant negative influence on the property prices. This situation may be based on privacy. According to Fahey (2016), the cost of renting a one-bedroom house is more than for a two-bedroom house. However, there is no marginal house size to measure the influences of the number of bedrooms. Investigating whether a 100-square-meter one-bedroom house is more expensive than an 80-square-meter two-bedroom house, for instance, would be an interesting subject for future research.

In Chapter 4, mortgage payment rates were shown to have a significant negative influence on property prices. The House Price Index (HPI), on the other hand, has a positive influence on property prices. It was also found that the average income of citizens influences property prices significantly and positively. These factors are related to economic performance in terms of property price and are statistically significant, as well as consistent with previous studies (Antolin and Bover, 1997; Lee, 1997; Chen and Patel, 1998; Shiller, 2007; Mints, 2007; Miles, 2008). Combining the developments in real estate in China, the Chinese government issued the "Notice on Strengthening Commercial Real Estate Credit Management", which had a significant effect on curbing high house prices. Further research could analyse the degree to which this policy affected prices. Whether the endogenous variables of economic fundamentals in this particular time have different levels of influence on house prices would be a significant question for future research. Moreover, the time taken for the real estate market to respond to policies is worthy of analysis.

Chapter 5 analyses the spatial statistics of house prices in Beijing, with the spatial autoregressive model (SAR), spatial Durbin model (SDM), a spatial autoregressive model with autoregressive disturbances (SAC) and spatial error model (SEM). The first significant step of the spatial analysis is to establish the spatial matrix in order to observe the spatial variation of house prices. The spatial weight matrix depicts the relationship between an element and elements in surrounding regions. The relevant dimension of the weight matrix defines the number of neighbours that influence the element in this weight matrix. Several methods can define the dimension of the weight matrix, such as inverse distance, fixed distance, K nearest neighbours, and contiguity to set for neighbourhood effects. This chapter employs queen contiguity spatial weight for the model based on the data characteristics, which are the polygons data of districts in Beijing, such as the average income of Chaoyang district. However, a previous study (Hoshino and Kuriyama, 2010) estimated the relative distance that was regarded as a standard of the weight matrix in spatial error model (SEM). For further research, it is suggested to employ different spatial weight matrices to check the influence of variables on the house prices. It is possible that the alternative weight matrix is the determinant of different spatial models, in reference to the tests of spatial dependence.

For future research, the selection of independent variables which was examined in Chapter 5 could be extended. This investigation employs GDP, unemployment rate, central bank interest rate, number of new projects, size of building started, average wage, distance to Beijing Capital Airport (km), distance to CBD (km), tax and urban population as the independent variables. Based on the data characteristics and data limitation, the calculation of distance has an error. For instance, this investigation regards polygons data, which are the average value of variables in each district, as the objective. The central location of each district is defined as the coordinate of the district. Thus, the distance to CBD is the distance between the centre of the district and the centre of CBD. In further research, the type of data can be diversified so to extend the independent variables. The other kinds of spatial data are points, lines and pixels. With reference to the development of the real estate market in China, data is limited. If this investigation were to use point's data for a longer period, the analysis would be more accurate and more interesting. The point data, which can be regarded as the house location, enhance the surrounding characteristics, such as the distance from the house to schools, the distance to shopping centres, the green ratio of the house, and the number of parking spaces allocated to the house. The more details specified about the house, the more accurate the measure of variation of house prices will be.

Future research could extend the work presented in Chapter 5 by exploring the spatial analysis of house prices combined with events consideration. For instance, in this investigation, the evidence is found for spatial dependence of house prices: house prices in one region are influenced by the house prices in neighbouring regions positively and significantly. The evidence is found for spatial heterogeneity of house prices across space: house prices spill-over to a greater extent when neighbouring house prices are increasing than when neighbouring house prices are declining. The evidence is found for spatial spill-over effects of explanatory factors: increases of the average wage, income, tax, urban population and house price of last year increase the house price positively in neighbouring regions; a decrease of unemployment drives down the house prices in neighbouring regions. These factors have spill-over effects across space. This investigation does not include event influences on house prices. In 2007, Shenzhen Bay Bridge, which connects Shenzhen and the west of Hong Kong, was established. After 2007, house prices of Shenzhen increased rapidly. The reason for that increase was the demand for Shenzhen houses by Hong Kong citizens. The construction of Shenzhen Bay Bridge enabled traffic to pass much more conveniently between Shenzhen and Hong Kong. Subsequently, increasing numbers of Hong Kong citizens bought houses in Shenzhen to avoid the high Hong Kong house prices. Thus, it is suggested that the influences of events on house prices are a further topic for research. This investigation examined the partitioning of direct and indirect effects to determine the impact on property prices of characteristics from nearby neighbours, to those which are more distant. Future research could also employ this method to test the range of event influences on house prices.

Chapter 6 of this investigation provides evidence that there are real options in China's real estate markets. Uncertainty about future prices drives up land prices in China. The investigation establishes a spatial method which also considered the effects of surrounding house prices and surrounding economic factors in order to improve the accuracy of house price uncertainty estimation. For further research, it is suggested to include surrounding environmental effects on house prices such as ratio of crime, ratio of causes of disease, and both CO_2 and air pollution indices. These determinants also improve the uncertainties which influence house price. On the other hand, the uncertainties can be obtained by alternative methods such as spatial autoregressive model (SAR), spatial autoregressive with autoregressive disturbances model (SAC) and spatial error model (SEM). This investigation suggests that real estate investors do account for real options, even in competitive and economically important sectors such as new home construction. The presence of real options in land markets is further evidence for the necessary inclusion of real options in models of capital investment and has broader implications for the importance of price stability and consistent government policy in stimulating fixed investment.

References

Abate, G. D. (2017). Spatio-temporal dynamics of house prices in the USA. *Letters in Spatial and Resource Sciences, 10*(2), 141-147.

Abercrombie, P. (1959). *Town and country planning* (D. R. Childs, 3rd Ed.). London: Oxford University Press.

Alonso, W. (1964). The historic and the structural theories of urban form: their implications for urban renewal. *Land Economics, 40*(2), 227-231.

Anenberg, E. (2011). Loss aversion, equity constraints and seller behaviour in the real estate market. *Regional Science and Urban Economics, 41*(1), 67-76.

Anglin, P. M., Dale-Johnson, D., Gao, Y., & Zhu, G. (2014). Patterns of growth in Chinese cities: Implications of the land lease. *Journal of Urban Economics, 83*(1), 87-107.

Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical Analysis, 20*(1), 1-17.

Anselin, L. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. *International Regional Science Review, 26*(2), 153-166.

Anselin, L., Florax, R., & Rey, S.J. eds. (2013). *Advances in spatial econometrics: methodology, tools and applications*. Springer Science & Business Media.

Anselin, L., Gallo, J., & Jayet, H. (2008). Spatial panel econometrics. In L. Matyas, & P. Sevestre (Eds.), *The Econometrics of panel data* (pp. 625-660). Berlin: Springer.

Antolin, P., & Bover, O. (1997). Regional migration in Spain: the effect of personal characteristics and unemployment, wage and house price differentials using pooled cross-sections. *Oxford Bulletin of Economics and Statistics, 59*(2), 215-235.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Review of Economic Studies, 68*(1), 29-51.

Autant-Bernard, C., & LeSage, J. P. (2011). Quantifying knowledge spillovers using spatial econometric models. *Journal of regional Science, 51*(3), 471-496.

Bailey, M. J., Muth, R. F., & Nourse, H. O. (1963). A regression method for real estate price index construction. *Journal of the American Statistical Association, 58*(304), 933-942.

Bajari, P., Cooley, J., & Timmins, C. (2010). A theory-based approach to hedonic price regressions with time-varying unobserved product attributes: The price of pollution (No. w15724). *National Bureau of Economic Research*.

Bajari, P., Fruehwirth, J. C., Kim, K. I., & Timmins, C. (2012). A rational expectations approach to hedonic price regressions with time-varying unobserved product attributes: The price of pollution. *The American Economic Review, 102*(5), 1898-1926.

Baltagi, B. (2001). *Econometric analysis of panel data*. Chichester: John Wiley and Sons Ltd.

Baltagi, B. (2013). *Econometric analysis of panel data* (5th ed.). UK: John Wiley & Sons.

Baltagi, B. H., Fingleton, B., & Pirotte, A. (2014). Spatial lag models with nested random effects: An instrumental variable procedure with an application to English house prices. *Journal of Urban Economics, 80*, 76-86.

Banerjee, S., Güçbilmez, U., & Pawlina, G. (2014). Optimal exercise of jointly held real options: A Nash bargaining approach with value diversion. *European Journal of Operational Research, 239*(2), 565-578.

Baranov, A., & Muzyko, E. (2015). Valuation of compound real options for investments in innovative projects in pharmaceutical industry. *Procedia Economics and Finance, 27*, 116-125.

Barbopoulos, L. G., Cheng, L. T., Cheng, Y., & Marshall, A. (2019). The role of real options in the takeover premia in mergers and acquisitions. *International Review of Economics & Finance, 61*, 91-107.

Barth, J. R., Lea, M., & Li, T. (2012). *China's Housing Market: Is a Bubble about to Burst?* Santa Monica: Milken Institute.

Basu, S., & Thibodeau, T. G. (1998). Analysis of Spatial Autocorrelation in House Prices. *Journal of Real Estate Finance and Economics, 17*(1), 61-85.

Baumont, C. (2004). Spatial effects in housing price models: do housing prices capitalize urban development policies in the agglomeration of Dijon (1999)?

Bernanke, B. S. (1983). Non-monetary effects of the financial crisis in the propagation of the Great Depression.

Bhattacharjee, A., Castro, E., Maiti, T., & Marques, J. (2016). Endogenous spatial regression and delineation of submarkets: a new framework with application to house markets. *Journal of Applied Econometrics, 31*(1), 32-57.

Black, A., Fraser, P., & Hoesli, M. (2006). House prices, fundamentals and bubbles. *Journal of Business Finance & Accounting, 33*(9/10), 1535-1555.

Black, F., & Scholes, M. (1973). The pricing of options on corporate liabilities. *The Journal of Political Economy, 81*(3), 637-659.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics, 31*(3), 307-327.

Boots, B., & Okabe, A. (2007). Local statistical analysis: Inventory and prospect. *International Journal of Geographical Information Science, 21*(4) 355-375.

Bourassa, S., Haurin, D., Haurin, J., Hoesli, M., & Sun, J. (2009). House price changes and idiosyncratic risk: The impact of property characteristics. *Real Estate Economics, 37*(2), 259-278.

Brady, R. R. (2014). The spatial diffusion of regional housing prices across US states. *Regional Science and Urban Economics, 46*, 150-166.

Bray, D. (2005). *Social space and governance in urban china: the Danwei system from origins to reform*. Stanford: Stanford University Press.

Brennan, M. J., & Schwartz, E. S. (1985). Evaluating natural resource investments. *Journal of business, 58*(2), 135.

Brunsdon, C., Fotheringham, A. S., Charlton, M. E. (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geogr. Anal., 28*, 281-298.

Bulan, L., Mayer, C., & Somerville, C. T. (2009). Irreversible investment, real options, and competition: Evidence from real estate development. *Journal of Urban Economics, 65*(3), 237-251.

Burgess, E. W. (1925). *The growth of the city: an introduction to a research project*. Chicago: University of Chicago Press.

Burnside, C., Martin, E., & Sergio, R. (2011). *Understanding booms and busts in house markets*. National Bureau of Economic Research Working Paper 16734.

Cameron, A. C., & Trivedi, P. K. (2009). *Microeconometrics using Stata*. Texas: StataCorp LP.

Campbell, J., & Shiller, R. (1987). Cointegration and tests of present value models. *Journal of Political Economy, 95*(10), 1062-1088.

Capozza, D. R., & Li, Y. (2002). Optimal land development decisions. *Journal of Urban Economics, 51*(1), 123-142.

Capozza, D. R., & Schwann, G. (1990). The value of risk in real estate markets. *Journal of Real Estate Finance and Economics, 3*(2), 117-140.

Capozza, D. R., Hendershott, P. H., & Mack, C. (2004). An anatomy of price dynamics in illiquid markets: analysis and evidence from local house markets. *Real Estate Economics, 32*(1), 1-32.

Carlino, G., & DeFina, R. (1998). The differential regional effects of monetary policy. *The* *review of economics and statistics, 80*(4), 572-587.

Carr, P., & Chen, R. R. (1988). Valuing bond futures and the quality option (Vol. 88, No. 22). Cornell University, Johnson Graduate School of Management.

Carrillo, P. E., Early, D. W., & Olsen, E. O. (2014). A panel of interarea price indices for all areas in the United States 1982-2012. *Journal of Housing Economics, 26*(1), 81-93.

Carrillo, P. E., Early, D. W., & Olsen, E. O. (2014). A panel of interarea price indices for all areas in the United States 1982–2012. *Journal of Housing Economics, 26*, 81-93.

Case, K. E., & Shiller, R. J. (1989). The efficiency of the market for single-family homes. *American Economic Review, 79*(1), 125-137.

Case, K. E., & Shiller, R. J. (1990). Forecasting prices and excess returns in the house market. *Journal of the American Real Estate and Urban Economics Association, 18*(3), 253-273.

Case, K. E., & Shiller, R. J. (2003). Is there a bubble in the house market. *Brookings Papers on Economic Activity, 1*(2), 299-362.

Chai, Y. (1996). *Danwei-centered activity space in Chinese cities: A case study of Lanzhou* (in Chinese). *Geography Research, 15*(1), 30-38.

Chang, C. O., Chen, M. C., & Deng, Y. (2008). *How much price bubbles are there in Taipei's real estate.* Papers of the 1st Global Chinese Real Estate Congress, Shanghai, China.

Chen, J., & Hao, Q. (2008). The Impacts of Distance to CBD on House prices in Shanghai. *Chinese Economic and Business Studies, 6*(3), 291-302.

Chen, J., & Li, X. (2011). *The income elasticity of house prices in China and its regional diversity*. Shanghai: School of Management, Fudan University.

Chen, J., Guo, F., & Wu, Y. (2011). One decade of urban housing reform in China: Urban house price dynamics and the role of migration and urbanization, 1995-2005. *Habitat International, 35*(1), 1-8.

Chen, M. C., & Patel, K. (1998). House price dynamics and granger causality: an analysis of Taipei new dwelling market. *International Real Estate Review, 1*(1), 101-126.

Chen, M., Zhang, W., & Lu, D. (2015). Examining spatial pattern and location choice of affordable housing in Beijing, China: Developing a workable assessment framework. *Urban Studies, 52*(10), 1846-1863.

Chen, R. D., Gan, C., Hu, B., & Cohen, D. A. (2012). An Empirical Analysis of House Price Bubble: A Case Study of Beijing Housing Market. *Research in Applied Economics, 5*(1), 1948-5433.

Chen, W. Y., & Jim, C. Y. (2010). Amenities and disamenities: a hedonic analysis of the heterogeneous urban landscape in Shenzhen (China). *Geography Journal, 176*(3), 227-240.

Cheng, I., Raina, S., & Xiong, W. (2014). Wall street and the housing bubble. *American Economic Review, 104*(9), 2797-2829.

Chiang, Y. H., Joinkey So, C. K., & Stanley Yeung, C. W. (2006). Real option premium in Hong Kong land prices. *Journal of Property Investment & Finance, 24*(3), 239-258.

Chow, W. W., Fung, M. K., & Cheng, A. C. (2016). Convergence and spillover of house prices in Chinese cities. *Applied Economics, 48*(51), 4922-4941.

Chung, K., & Charoenwong C. (1991). Investment Options, Assets in Place, and Risk of Stocks. *Financial Management,* 20(3), 21-33.

Čirjevskis, A., & Tatevosjans, E. (2015). Empirical Testing of Real Option in the Real Estate Market. *Procedia Economics and Finance, 24*, 50-59.

Clapp, J. M., Kim, H. J., & Gelfand, A. E. (2002). Predicting spatial patterns of house prices using LPR and Bayesian smoothing. *Real Estate Economics, 30*(4), 505-532.

Clark, E., Gadad, M., & Rousseau, P. (2010). Investor valuation of the abandonment option: Empirical evidence from UK divestitures 1985-1991. *Multinational Finance Journal, 14*(3/4), 291-317.

Clark, S. D. (2007) Estimating local car ownership models. *Journal of Transport Geography, 15*(3) 184-197.

Cliff, A., & Ord, J.K. (1973). *Spatial Autocorrelation*. London: Pion.

Cohen, J. P., Ioannides, Y. M., & Thanapisitikul, W. W. (2016). Spatial effects and house price dynamics in the USA. *Journal of Housing Economics, 31*, 1-13.

Costello, G., Fraser, P., & Groenewold, N. (2011). House prices, non-fundamental components and interstate spillovers: The Australian experience. *Journal of Banking & Finance, 35*(3), 653-669.

Crundwell, F. (2008). *Finance for engineers: Evaluation and funding of capital projects*. Springer Science & Business Media.

Cunningham, C. R. (2006). House price uncertainty, timing of development, and vacant land prices: Evidence for real options in Seattle. *Journal of Urban Economics, 59*(1), 1-31.

Cunningham, C. R. (2007). Growth controls, real options, and land development. *The Review of Economics and Statistics, 89*(2), 343-358.

Deng, Y., Girardin, E., & Joyeux, R. (2018). Fundamentals and the volatility of real estate prices in China: A sequential modelling strategy. *China Economic Review, 48*, 205-222.

Deng, Y., Morck, R., Wu, J., & Yeung, B. (2015). China's pseudo-monetary policy. Review of Finance, 19, 55-93.

DeSilva, S., Pham, A., & Smith, M. (2012). Racial and ethnic price differentials in a small urban housing market. *Housing Policy Debate 22*(2), 241-269.

Di Corato, L., & Brady, M. V. (2019). Passive farming and land development: A real options approach. *Land Use Policy, 80*, 32-46.

Diba, B. T., & Grossman, H. I. (1988). Explosive rational bubbles in stock prices. *American Economic Review, 78*(3), 520-530.

Dieleman, F. M., Clark, W. A. V., & Deurloo, M. C. (2000). The geography of residential turnover in twenty-seven large US metropolitan house markets, 1985-1995. *Urban Studies, 37*(2), 223-245.

Dixit, A. (1989). Entry and exit decisions under uncertainty. *Journal of political Economy, 97*(3), 620-638.

Dixit, A. K., Dixit, R. K., & Pindyck, R. S. (1994). *Investment under uncertainty*. US: Princeton university press.

Doh, J. P., & Hahn, E. D. (2008). Using spatial methods in strategy research. *Organizational Research Methods, 11*(4) 659-681.

Dokko, J., Doyle, B. M., Kiley, M. T., Kim, J., Sherlund, S., Sim, J., & Heuvel, S. V. D. (2011). Monetary policy and the global housing bubble. *Economic Policy, 26*(66), 233-283.

Dong, G. P., & Zhang, W. Z. (2011). Spatial heterogeneity in determinants of residential land price: simulation and prediction. *Geography Journal, 66*(6), 750-760. (in Chinese)

Drachal, K. (2016). House prices and unemployment: A recent evidence from Poland. *Urbanism. Arhitectura. Constructii, 7*(1), 43-56.

Du, X., & Huang, Z. (2018). Spatial and temporal effects of urban wetlands on housing prices: Evidence from Hangzhou, China. *Land use policy, 73*, 290-298.

Elhorst, J. P. (2001). Dynamic models in space and time. *Geographical Analysis, 33*(2), 119-140.

Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. *Spatial Economic Analysis, 5*(1), 1742-1780.

Elhorst, J. P. (2010). Matlab software for spatial panels. In Paper presented at the 4th World Conference of the Spatial Econometrics Association (SEA). Chicago.

Elhorst, J. P. (2014). Spatial panel data models. In *Spatial econometrics* (pp. 37-93). Berlin: Springer.

Elhorst, J. P. (2014). *Spatial panel data models*. In Spatial econometrics (pp. 37-93). Berlin: Springer.

Engelhardt, G. V. (2003). Nominal loss aversion, housing equity constraints, and household mobility: Evidence from the United States. *Journal of Urban Economics, 53*(1), 171-195.

Eriksen, M. D., & Rosenthal, S. S. (2010). Crowd out effects of place-based subsidized rental housing: New evidence from the LIHTC program. *Journal of Public Economics, 94*(11), 953-966.

Evans, A. W. (1973). *The economics of residential location*. London: The Macmillan Press Ltd.

Fahey, M. (2016). *It's getting very expensive to live alone in America*. Retrieved from https://www.cnbc.com/2016/09/15/its-getting-very-expensive-to-live-alone.html.

Fan, G. Z., Pu, M., Deng, X., & Ong, S. E. (2018). Optimal portfolio choices and the determination of housing rents under housing market uncertainty. *Journal of Housing Economics, 41*, 200-217.

Fang, H., Gu, Q., Xiong, W., & Zhou, L. A. (2016). Demystifying the Chinese housing boom. *NBER Macroeconomics Annual, 30*(1), 105-166.

Farlow, A. (2004). *UK house prices: A critical assessment*. London: Credit Suisse First Boston (CSFB).

Feltenstein, A., & Farhadian, Z. (1987). Fiscal policy, monetary targets, and the price level in a centrally planned economy: an application to the case of China. *Journal of Money, Credit and Banking, 19*(2), 137-156.

Fereidouni, H. G., Al-Mulali, U., Lee, J. Y., & Mohammed, A. H. (2016). Dynamic Relationship between House Prices in Malaysia’s Major Economic Regions and Singapore House Prices. *Regional Studies, 50*(4), 657-670.

Fernandes, R., Gouveia, B., & Pinho, C. (2013). A real options approach to labour shifts planning under different service level targets. *European Journal of Operational Research, 231*(1), 182-189.

Fernandez, L., Mukherjee, M., & Scott, T. (2018). The effect of conservation policy and varied open space on residential property values: A dynamic hedonic analysis. *Land use policy, 73*, 480-487.

Fernández-Kranz, D., & Hon, M. T. (2006) Across-section analysis of the income elasticity of housing demand in Spain: Is there a real estate bubble. *Journal of Real Estate Finance and Economics, 32*(4), 449-470.

Festinger, L. (1957). *A theory of cognitive dissonance*. Redwood City, CA: Stanford University Press.

Fonseca, M. N., de Oliveira Pamplona, E., de Mello Valerio, V. E., Aquila, G., Rocha, L.C.S., & Junior, P. R. (2017). Oil price volatility: A real option valuation approach in an African oil field. *Journal of Petroleum Science and Engineering, 150*, 297-304.

Foo Sing, T., & Patel, K. (2001). Empirical evaluation of the value of waiting to invest. *Journal of Property Investment & Finance, 19*(6), 535-553.

Fotheringham, A. S., Brunsdon, C., & Charlton M. (2000). *Quantitative Geography - Perspectives on Spatial Data Analysis*. London: Sage Publications.

Fotheringham, A. S., Charlton, M., & Brunsdon, C. (1997). *Measuring Spatial Variations in Relationships with Geographically Weighted Regression*. Germany: Springer: Berlin/Heidelberg.

Fratantoni, M., & Schuh, S. (2003). Monetary policy, housing, and heterogeneous regional markets. *Journal of Money, Credit, and Banking, 35*(4), 557-589.

Galbraith, J. K. (1958). *The affluent society*. London: Hamish Hamilton.

Gan, C., Li, Z., Wang, W., & Kao, B. (2012). Credit scoring in mortgage lending: evidence from China. *International Journal of Housing Markets and Analysis, 5*(4), 334-350.

Gan, L., Yin, Z., & Zang, W. (2010). The impact of housing reform on durables consumption in China. *China Economic Review, 21*, S55-S64.

Gao, X. L., & Yasushi, A. (2011). Preferential size of housing in Beijing. *Habitat International, 35*(1), 206-213.

Garriga, C., Hedlund, A., Tang, Y., & Wang, P. (2017). Rural-urban migration, structural transformation, and housing markets in China (No. w23819). *National Bureau of Economic Research*.

Ge, T., & Wu, T. (2017). Urbanization, inequality and property prices: Equilibrium pricing and transaction in the Chinese housing market. *China Economic Review, 45*, 310-328.

Genesove, D., & Mayer, C. (2001). Loss aversion and seller behaviour: Evidence from the house market. *The Quarterly Journal of Economics, 116*(4), 1233-1260.

Gennaioli, N., Andrei S., & Robert, W. V. (2013). A model of shadow banking. *Journal of Finance, 68*(4), 1331-1363.

Gibbons, S., & Overman, H. G. (2012). Mostly pointless spatial econometrics? *Journal of Regional Science, 52*(2), 172-191.

Giussani, B., & Hadjimatheou, G. (1991). Modeling regional house prices in the United Kingdom. *Papers in Regional Science, 70*(2), 201-219.

Glaeser, E. L., Kahn, M. E., & Rappaport, J. (2008). Why do the poor live in cities? The role of public transportation. *Journal of Urban Economics, 63*(1), 1-24.

Glaeser, E., Huang, W., Ma, Y., & Shleifer, A. (2017). A real estate boom with Chinese characteristics. *Journal of Economic Perspectives, 31*(1), 93-116.

Gong, Y., Boelhouwer, P. J., & de Haan, J. (2015). Interurban house price gradient: Effect of urban hierarchy distance on house prices. *Urban Studies, 53*(15), 3317-3335.

Gong, Y., Hu, J., & Boelhouwer, P. J. (2016). Spatial interrelations of Chinese housing markets: Spatial causality, convergence and diffusion. *Regional Science and Urban Economics, 59*(2), 103-117.

Goodchild, M. F. (2009). *Challenges in spatial analysis, in A.S. Fotheringham and P.A. Rogerson (eds.)*. The Sage Handbook of Spatial Analysis, 465-477. London: Sage.

Granger, C., & Engle, R. (1987). Cointegration and the error-correction representation: estimation and testing. *Econometrica*, *55*(1), 251-76.

Grovenstein, R. A., Kau, J. B., & Munneke, H. J. (2011). Development value: a real options approach using empirical data. *The Journal of Real Estate Finance and Economics, 43*(3), 321-335.

Guo, K., Wang, J., Shi, G., & Cao, X. (2012). Cluster analysis on city real estate market of China: based on a new integrated method for time series clustering. *Procedia Computer Science, 9*(1), 1299-1305.

Hamill, P. A., McIlkenny, P., & Opong, K. K. (2013). Valuation implications of pharmaceutical companies' R&D regulatory approval notifications. *The British Accounting Review, 45*(2), 99-111.

Hanink, D. M., Cromley, R. G., & Ebenstein, A. Y. (2012). Spatial variation in the determinants of house prices and apartment rents in China. *The Journal of Real Estate Finance and Economics, 45*(2), 347-363.

Harris, R., Dong, G., & Zhang, W. (2013). Using Contextualized Geographically Weighted R egression to Model the Spatial Heterogeneity of Land Prices in Beijing, China. *Transactions in GIS, 17*(6), 901-919.

Hartmann, M., & Hassan, A. (2006). Application of real options analysis for pharmaceutical R&D project valuation - Empirical results from a survey. *Research Policy, 35*(3), 343-354.

Helbich, M., Brunauer, W. Vaz, E. & Nijkamp, P. (2014). Spatial heterogeneity in hedonic house price models: The case of Austria. *Urban Studies, 51*, 390-411.

Hillebrand, M., & Kikuchi, T. (2015). A mechanism for booms and busts in house prices.

Journal of Economic Dynamics and Control, 51, 204-217.

Himmelberg, C., Mayer, C., & Sinai, T. (2005). Assessing high house prices: bubbles, fundamentals and misperceptions. *Journal of Economic Perspective, 19*(4), 67-92.

Holland, A. S., Ott, S. H., & Riddiough, T. J. (2000). The role of uncertainty in investment: An examination of competing investment models using commercial real estate data. *Real Estate Economics, 28*(1), 33-64.

Holly, S., Pesaran, M. H., & Yamagata, T. (2011). The spatial and temporal diffusion of house prices in the UK. *Journal of Urban Economics, 69*(1), 2-23.

Hori, K., & Osano, H. (2010). *Optimal executive compensation and investment timing*. Working paper at SSRN.

Horioka, C. Y., & Wan, J. (2007). The determinants of household saving in China: a dynamic panel analysis of provincial data. *Journal of Money, Credit and Banking, 39*(8), 2077-2096.

Hoshino, T., & Kuriyama, K. (2010). Measuring the benefits of neighborhood park amenities: Application and comparison of spatial hedonic approaches. *Environmental and Resource Economics, 45*(3), 429-444.

Host, G. (1999). Kriging by local polynomials. *Computational Statistics & Data Analysis, 29*(3), 295-312.

Hoyt, W. H. (I939). *The structure and growth of residential neighbourhoods in American cities*. Washington: U.S. Government Printing Office.

Hoyt, W. H., & Rosenthal, S. S. (1990). Capital gains taxation and the demand for owner-occupied housing. *The Review of Economics and Statistics*, 45-54.

Huang, H., & Yin, L. (2015). Creating sustainable urban built environments: An application of hedonic house price models in Wuhan, China. *Journal of Housing and the Built Environment, 30*(2), 219-235.

Huang, J., & Rong, Z. (2017). Housing boom, real estate diversification, and capital structure: Evidence from China. *Emerging Markets Review, 32*, 74-95.

Huang, N., Li, J., & Ross, A. (2018). The impact of the cost of car ownership on the house price gradient in Singapore. *Regional Science and Urban Economics, 68*, 160-171.

Huang, Z., Chen, R., Xu, D., & Zhou, W. (2017). Spatial and hedonic analysis of house prices in Shanghai. *Habitat International, 67*, 69-78.

Hui, E. C. M., & Fung, H. H. K. (2009). Real estate development as real options. *Construction Management and Economics, 27*(1), 221-227.

Hui, E. C. M., & Gu, Q. (2009). Study of Guangzhou house price bubble based on state-space model. *International Journal of Strategic Property Management, 13*(1), 287-298.

Hui, E. C. M., & Ng, I. (2009). Price discovery of property markets in Shenzhen and Hong Kong. *Construction Management and Economics, 27*, 1175-1196.

Hui, E. C. M., & Yue, S. (2006). House price bubbles in Hong Kong, Beijing and Shanghai: A comparative study. *Journal of Real Estate Finance and Economics, 33*(4), 299-327.

Hund, L., Bedrick, E. J., Miller, C., Huerta, G., Nez, T., Ramone, S., Shuey, C., Cajero, M., & Lewis, J. (2015). A Bayesian framework for estimating disease risk due to exposure to uranium mine and mill waste on the Navajo Nation. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 178*(4), 1069-1091.

Hyun, D., & Milcheva, S. (2018). Spatial dependence in apartment transaction prices during boom and bust. *Regional Science and Urban Economics, 68*, 36-45.

Ingersoll, J. E., & Ross, S. A. (1992). Waiting to invest: Investment and uncertainty. *Journal of Business*, 1-29.

Irving, F. (1911). *The purchasing power of money*. New York: Macmillan.

Isard, W. (1956). *Location and space-economy*. Cambridge The MIT Press.

Ismail, S. (2006). Spatial autocorrelation and real estate studies: A literature review. *Malaysian Journal of Real Estate, 1*(1), 1-13.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305-360.

Jim, C. Y., & Chen, W. Y. (2006). Impacts of urban environmental elements on residential housing prices in Guangzhou (China). *Landscape Urban Planning, 78*(4), 422-434.

Jim, C. Y., & Chen, W. Y. (2009). Value of scenic views: Hedonic assessment of private housing in Hong Kong. *Landscape and Urban Planning, 91*(1), 226-234.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263-291.

Karami, M., & Farsani, F. A. (2011). Real option method and escalation of commitment in the evaluation of investment projects. *American Journal of Economics and Business Administration, 3*(3), 473.

Kelejian, H. H., & Prucha, I. R. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics, 157*(1), 53-67.

Kellogg, C. F., & Dietrich, A. T. (2000). Swing door seal and retainer assembly having a seal with interior webs. *U.S. Patent, 6*,158-171.

Keswani, A., & Shackleton, M.B. (2006). How real option disinvestment flexibility augments project NPV. *European Journal of Operational Research, 168*(1), 240-252.

Kim, C. W., Phipps, T. T., & Anselin, L. (2003). Measuring the benefits of air quality improvement: a spatial hedonic approach. *Journal of Environmental Economics and Management, 45*(1), 24-39.

Kim, K., Ha, S., & Kim, H. (2017). Using real options for urban infrastructure adaptation under climate change. *Journal of cleaner production, 143*, 40-50.

Kissling, W. D., & Carl, G. (2008). Spatial autocorrelation and the selection of simultaneous autoregressive models. *Global Ecology and Biogeography, 17* (1), 59-71.

Klugman, S. A., Panjer, H. H., & Willmot, G.E. (2012). Loss models: From data to decisions (Vol. 715). John Wiley & Sons.

Kohn, J., & Bryant, S. K. (2010). Factors leading to the U.S. housing bubble: a structural equation modelling approach. *Research in Business and Economics Journal, 3*(1), 1-20.

Kohn, J., & Bryant, S. K. (2010). Modeling the U.S. housing bubble: An econometric analysis. *Research in Business and Economics Journal, 2*(1), 1-14.

Kondo, K. (2015). Spatial persistence of Japanese unemployment rates. *Japan and the World Economy, 36*, 113-122.

Köppl, S. (2013). Real options for agricultural investments. *Metody Ilościowe w Badaniach Ekonomicznych, 14*(1), 253-264.

Koss, R., & Shi, X. (2018). Stabilizing China's housing market. *International Monetary Fund*.

Kuethe, T., & Pede, V. (2011). Regional house price cycles: A spatio-temporal analysis using US state-level data. *Regional Studies, 45*(5), 563-574.

Lander, D. M., & Pinches, G. E. (1998). Challenges to the practical implementation of modelling and valuing real options. *Quarterly Review of Economics and Finance, 38*(Special Issue), 537-567.

Larraz-Iribas, B., & Alfaro-Navarro, J. (2008). Asymmetric behaviour of Spanish regional house prices. *International Advances in Economic Research, 14*(4), 407-421.

Lee, C. L., & Reed, R. (2013). Volatility decomposition of Australian housing prices. *Journal of Housing Research, 23*(1), 21-43.

Lee, J. S. (1997). An Ordo-liberal perspective on land problems in Korea. *Urban Studies, 34*(7), 1071-1084.

Lee, L. F., & Yu, J. (2010). Some recent developments in spatial panel data models. *Regional*

Science and Urban Economics, 40(5), 255-271.

Lei, V., Noussair C., & Plott C. (2001). Non-speculative bubbles in experimental asset markets: lack of common knowledge of rationality vs actual irrationality. *Econometrica, 69*(1), 831-859.

LeSage, J. P., & Pace, R. K. (2009). Introduction to spatial econometrics. Boca Raton: Chapman & Hall/CRC.

LeSage, J. P., & Pace, R. K. (2010). *Spatial econometric models*. In Handbook of applied spatial analysis (pp. 355-376). Berlin: Springer.

Li, D., Chen, H., Hui, E. C. M., Xiao, C., Cui, Q., & Li, Q. (2014). A real option-based valuation model for privately-owned public rental housing projects in China. *Habitat International, 43*, 125-132.

Li, Q., & Chand, S. (2013). House prices and market fundamentals in urban China. *Habitat International, 40*(1), 148-153.

Li, X., & Yuan, D. P. (2012). The process and main difficulties of the system of housing in China (in Chinese). *Reformation and Strategy, 28*(203), 13-18.

Li, Z., Razali, M. N., Fereidouni, H. G., & Adnan, Y. M. (2018). Macro-economic index effect on house prices in China. *International Journal of Housing Markets and Analysis, 11*(3), 453-475.

Liu, C., & Xiong, W. (2018). China's Real Estate Market (No. w25297). *National Bureau of Economic Research*.

Liu, J., Yang, Y., Xu, S., Zhao, Y., Wang, Y., & Zhang, F. (2016). A geographically temporal weighted regression approach with travel distance for house price estimation. *Entropy, 18*(8), 303.

Liu, X. (2013). Spatial and temporal dependence in house price prediction. *The Journal of Real Estate Finance and Economics, 47*(2), 341-369.

Lloyd, C. D. (2007). *Local Models for Spatial Analysis*. Boca Raton: CRC Press.

Losch, A. (1954). *The economics of Location* (W. H. Woglom, Trans.). New Haven: Yale University Press.

Lu, J. (2018). The value of a south-facing orientation: A hedonic pricing analysis of the Shanghai housing market. *Habitat International, 81*, 24-32.

Maisel, S. J. (1963). A theory of fluctuations in residential construction starts. *The American Economic Review, 53*(3), 359-383.

Majd, S., & Pindyck, R. S. (1987). Time to build, option value, and investment decisions. *Journal of financial Economics, 18*(1), 7-27.

Malpezzi, S. (2002). Hedonic pricing models: A selective and applied review. *Housing Economics and Public Policy, 1*, 67-74.

Mankiw, N. G., Romer, D., & Shapiro, M. D. (1985). An unbiased reexamination of stock market volatility. *Journal of Finance, 40*(3), 677-687.

Mayer, C., & Quigley, J. M. (2003). Comments and discussion: is there a bubble in the house market. *Brookings Papers on Economic Activity, 2*(1), 343-362.

McDonald, R., & Siegel, D. (1986). The value of waiting to invest. *The Quarterly Journal of Economics, 101*(4), 707-727.

McGrath, R. G., & Nerkar, A. (2004). Real options reasoning and a new look at the R&D investment strategies of pharmaceutical firms. *Strategic Management Journal, 25*(1), 1-21.

McGreal, S., & de La Paz, P. T. (2013). Implicit house prices: Variation over time and space in Spain. *Urban Studies, 50*(10), 2024-2043.

McMillen, D. P. (2012). Perspectives on spatial econometrics: linear smoothing with structured models. *Journal of Regional Science, 52*(2), 192-209.

Meen, G. (1996). Spatial aggregation, spatial dependence and predictability in the UK house market. *Housing Studies, 11*(3), 345-372.

Meen, G. (1999). Regional house prices and the ripple effect: A new interpretation. *Housing Studies, 14*(6), 733-753.

Merton, R. C. (1973). Theory of rational option pricing. *Bell Journal of Economics & Management, 4*(1), 141-183.

Miles, W. (2008). Boom-bust cycles and the forecasting performance of linear and non-linear models of house prices. *The Journal of Real Estate Finance and Economics, 36*(3), 249-264.

Miles, W. (2011). Clustering in UK home price volatility. *Journal of Housing Research, 20*(1), 87-101.

Milne, A. (1991). *Incomes, demography and UK house prices*. Centre for Economic Forecasting Discussion Paper, No 3090, London Business School.

Mints, V. (2007). The mortgage rate and housing bubbles. *Housing Finance International, 21*(4), 34.

Mou, Y., He, Q., & Zhou, B. (2017). Detecting the spatially non-stationary relationships between housing price and its determinants in China: Guide for housing market sustainability. *Sustainability, 9*(10), 1826.

Mussa, A., Nwaogu, U.G., & Pozo, S. (2017). Immigration and housing: A spatial econometric analysis. *Journal of Housing Economics, 35*(1), 13-25.

Myers, N. (1988). Threatened biotas: "hot spots" in tropical forests. *Environmentalist, 8*(3), 187-208.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics, 5*(2), 147-175.

Naylor, T. H. (1967). The impact of fiscal and monetary policy on the housing market. *Law and Contemporary Problems, 32*(3), 384-396.

Neelon, B., Gelfand, A. E., & Miranda, M. L. (2014). A multivariate spatial mixture model for areal data: examining regional differences in standardized test scores. *Journal of the Royal Statistical Society: Series C (Applied Statistics), 63*(5), 737-761.

Nishihara, M., & Shibata, T. (2008). The agency problem between the owner and the manager in real investment: The bonus-audit relationship. *Operations Research Letters, 36*(3), 291-296.

Novokmet, F., Piketty, T., Yang, L., & Zucman, G. (2018). From communism to capitalism: Private versus public property and inequality in China and Russia. *AEA Papers and Proceedings, 108*(1), 109-113.

Oikarinen, E. (2006). The diffusion of house price movements from center to surrounding areas. *Journal of Housing Research, 15*(1), 3-28.

Osland, L., & Thorsen, I. (2013). Spatial impacts, local labour market characteristics and housing prices. *Urban Studies, 50*(10), 2063-2083.

Pace, R. K., & Zhu, S. (2019). The influence of house, seller, and locational factors on the probability of sale. *Journal of Housing Economics, 43*, 72-82.

Peng, W., Tam, D., & Yiu, M. S. (2005). The property market and the macroeconomy of the mainland: A cross region study. *Hong Kong Institute for Monetary Research*.

Pijnenburg, K. (2017). The spatial dimension of US house prices. *Urban Studies, 54*(2), 466-481.

Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. *Journal of Economic Literature, 29*(1), 1110-1148.

Pindyck, R. S., & Rotemberg, J. J. (1988). The excess co-movement of commodity prices.

Qi, L., & Cao, H. (2007). Property prices and bank lending in China. *Journal of Asian Economics, 18*, 63-75.

Quigg, L. (1993). Empirical testing of real option-pricing models. *The Journal of Finance, 48*(2), 621-640.

Razak, M. Z., Khalid, H., & Mohamad, A. (2018). Speculative behavior in vacant land development: evidence for real options in Malaysia. *The Developing Economies, 56*(4), 245-266.

Ren, Y., Xiong, C., & Yuan, Y. (2012). House price bubbles in China. *China Economic Review, 23*, 786-800.

Richardson, H. (I971). *Urban economics*. London: Penguin Education.

Riddel, M. (2011). Are housing bubbles contagious? A case study of Las Vegas and Los Angeles home prices. *Land Economics, 87*(1), 126-144.

Riley, S. F., Nguyen, G., & Manturuk, K. (2015). House price dynamics, unemployment, and the mobility decisions of low-income homeowners. *Journal of Housing and the Built Environment, 30*(1), 141-156.

Riley, S., Nguyen, G., & Manturuk, K. (2015). House price dynamics, unemployment, and the mobility decisions of low-income homeowners. *Journal of Housing & the Built Environment, 30*(1), 141-156.

Rithmire, M. E. (2017). Land institutions and Chinese political economy: institutional complementarities and macroeconomic management. *Politics & Society, 45*(1), 123-153.

Rocha, K., Luciana, S., Francisco, A., & José, A.S. (2007). Real estate and real options: A case study. *Emerging Markets Review, 8*(1), 67-79.

Rosen, S. (1974). Wage-based indexes of urban quality of life. *Journal of urban economics*, 3.

Rosenthal, S. S. (2014). Are private markets and filtering a viable source of low-income housing? Estimates from a “repeat income” model. *American Economic Review, 104*(2), 687-706.

Rosenthal, S. S., Duca, J. V., & Gabriel, S. A. (1991). Credit rationing and the demand for owner-occupied housing. *Journal of Urban Economics, 30*(1), 48-63.

Sabet, A. H., & Heaney, R. (2017). Real options and the value of oil and gas firms: An empirical analysis. *Journal of Commodity Markets, 6*, 50-65.

Sanderson, T., Hertzler, G., Capon, T., & Hayman, P. (2016). A real options analysis of Australian wheat production under climate change. *Australian Journal of Agricultural and Resource Economics, 60*(1), 79-96.

Schwartz, E. S., & Trigeorgis, L. (2004). *Real options and investment under uncertainty: classical readings and recent contributions*. Cambridge: Massachusetts.

Seliske, L., Norwood, T. A., McLaughlin, J. R., Wang, S., Palleschi, C., & Holowaty, E. (2016). Estimating micro area behavioural risk factor prevalence from large population-based surveys: a full Bayesian approach. *BMC public health, 16*(1), 478.

Seyoum, E., & Chan, C. (2012). *A real-options analysis of wine grape farming in north west Victoria*. Conference paper in the 2012 annual conference of the Australian Agricultural and Resource Economics Society February 7-10, Fremantle, Western Australia.

Shaikh, A. M., & Tonak, E. A. (1997). *Measuring the wealth of nations*. Cambridge: Cambridge Books.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance, 40*(3), 777-790.

Sheik, A., & Vora, G. (1990). The robustness of volatilities implied by the Black-Scholes formula and using implied volatilities to infer the parameters of stock-price processes. Working paper, Indiana University.

Shen, Y., & Liu, H. Y. (2004). House price and economic fundamentals: a cross city analysis of China for 1995 to 2002. *Journal of Economics Research, 6*(1), 78-86.

Shepard, W. (2015). *Ghost cities of China: The story of cities without people in the world's most populated country*. London: Zed Books.

Shi, S., Yang, Z., Tripe, D., & Zhang, H. (2015). Uncertainty and new apartment price setting: A real options approach. *Pacific-Basin Finance Journal, 35*, 574-591.

Shi, W., & Lee, L. F. (2017). Spatial dynamic panel data models with interactive fixed effects. *Journal of Econometrics, 197*(2), 323-347.

Shi, W., & Lee, L. F. (2018). A spatial panel data model with time varying endogenous weights matrices and common factors. *Regional Science and Urban Economics, 72*(1), 6-34.

Shi, Y. S., & Zhang, R. (2010). Temporal-spatial impact effects of largescale parks on residential prices: exemplified by the Huangxing Park in Shanghai. *Geographical Residence, 29*(3), 510-520.

Shiller, R. J. (2007). *Understanding recent trends in house prices and home ownership*. Paper presented at the Federal Reserve Bank of Kansas City's Jackson Hole Symposium, Kansas City.

Small, K. A., & Steimetz, S. S. (2012). Spatial hedonic and the willingness to pay for residential amenities. *Journal of Regional Science, 52*(4), 635-647.

Smith, M. H., & Smith, G. (2006). Bubble, bubble, where's the housing bubble. *Brookings Papers on Economic Activity, 1*(1), 1-50.

Sutton, G. D. (2002). Explaining changes in house prices. *BIS Quarterly Review,* 46-55.

Tang, W., & Wang, Y. (2017). Incomplete information and real estate development strategy:

Evidence from Hangzhou, China. *Habitat International, 63*, 1-10.

Taylor, J. B. (2000). Reassessing discretionary fiscal policy. *Journal of economic Perspectives, 14*(3), 21-36.

Terán-Hernández, M., Ramis-Prieto, R., Calderón-Hernández, J., Garrocho-Rangel, C. F., Campos-Alanís, J., Ávalos-Lozano, J. A., & Aguilar-Robledo, M. (2016). Geographic variations in cervical cancer risk in San Luis Potosí state, Mexico: A spatial statistical approach. *International journal for equity in health, 15*(1), 161.

Teye, A. L., & Ahelegbey, D. F. (2017). Detecting spatial and temporal house price diffusion in the Netherlands: A Bayesian network approach. *Regional Science and Urban Economics, 65*, 56-64.

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral Decision Making, 12*(3), 183-206.

Titman, S. (1985). Urban land prices under uncertainty. *American Economic Review, 75*(3), 505-514.

Titman, S., & Torous, W. (1989). Valuing commercial mortgages: an empirical investigation of the contingent-claims approach to pricing risky debt. *The Journal of Finance, 44*(2), 345-373.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic geography, 46*(1), 234-240.

Trigeorgis, L. (1988). A conceptual options framework for capital budgeting. *Advances in Futures and Options Research, 3*(3), 145-164.

Trigeorgis, L. (1993). Real options and interactions with financial flexibility. *Financial management*, 202-224.

Trigeorgis, L. (1996). *Real options: Managerial flexibility and strategy in resource allocation*. US: MIT press.

Trigeorgis, L., & Mason, S. P. (1987). Valuing managerial flexibility. *Midland corporate finance journal, 5*(1), 14-21.

Tsekrekos, A. E., & Kanoutos, G. (2013). Real options premia implied from recent transactions in the Greek real estate market. *The Journal of Real Estate Finance and Economics, 47*(1), 152-168.

Turvey, R. (1957). *The economics of real property*. London: George Allen & Unwin.

Tzouramani, I., & Mattas, K. (2004). Employing real options methodology in agricultural investments: the case of greenhouse construction. *Applied Economics Letters, 11*(6), 355-359.

Vahdatmanesh, M., & Firouzi, A. (2017). *Real Options Valuation for Residential Real Estate Development Projects*. Conference paper on the 1st international & 3rd national conference of construction & project management, at Tehran.

Van Dijk, B., Franses, P. H., Paap, R., & Van Dijk, D. (2011). Modelling regional house prices. *Applied Economics, 43*(17), 2097-2110.

Veie, K. L., & Panduro, T. E. (2015). An alternative to the standard spatial econometric approaches in hedonic house price models. *Land Economics, 91*(2), 386-409.

Wang, F., & Gao, X. (2014). The transitional spatial pattern of house prices in Beijing: Factors and implications. *International review for spatial planning and sustainable development, 2*(3), 46-62.

Wang, S. Y. (2011). State misallocation and house prices: theory and evidence from China. *American Economic Review, 101*(5), 2081-2107.

Wang, S. Y. (2012). Credit constraints, job mobility, and entrepreneurship: Evidence from a property reform in China. *Review of Economics and Statistics, 94*(2), 532-551.

Wang, Y., Tang, W., & Jia, S. (2016). Uncertainty, competition and timing of land development: Theory and empirical evidence from Hangzhou, China. *The Journal of Real Estate Finance and Economics, 53*(2), 218-245.

Wang, Y., Wang, D., & Wei, Y. (2013). Spatial differentiation patterns of house price and house price-to-income ratio in China's cities. *In Proceedings of the 2013 21st International Conference* on Geoinformatics, Kaifeng, China.

Wang, Y., Wang, S., Li, G., Zhang, H., Jin, L., Su, Y., & Wu, K. (2017). Identifying the determinants of house prices in China using spatial regression and the geographical detector technique. *Appl. Geogr., 79*, 26-36.

Wang, Z., Zhang. Q., & Zhou, L. A. (2018). Career incentives of city leaders and urban spatial expansion in China. *Working paper*.

Wang. D., & Huang, W. H. (2007). Effect of urban environment on residential property values by hedonic method: a case study of shanghai. *Urban Planning, 31*(9), 34-41. (in Chinese)

Wen, H. Z., & Jia, S. H. (2004). Housing characteristics and hedonic price: based on hedonic price model. J. *Zhejiang University (English Science), 38*(10), 38-42.

Wen, H., & Goodman, A. C. (2013). Relationship between urban land price and house price: Evidence from 21 provincial capitals in China. *Habitat International, 40*(1), 9-17.

Wen, H., & Tao, Y. (2015). Polycentric urban structure and housing price in the transitional China: Evidence from Hangzhou. *Habitat International, 46*, 138-146.

Willcocks, G. (2010). UK housing market: time series processes with independent and identically distributed residuals. *Journal of Real Estate Finance and Economics, 39*(4), 403.

Wilson, C. A., & Parisi, A. V. (2006). Protection from solar erythemal ultraviolet radiation-simulated wear and laboratory testing. Textile Research *Journal, 76*(3), 216-225.

Wong, S. K., Wing, C. K., & Yau, Y. (2005). *Property price, floor level, and building density*. Paper presented at the 6th International Conference on Tall Buildings, Hong Kong. Retrieved from http://www.graphics.stanford.edu/papers/twohanded/.

Wood, R. (2003). The information content of regional house prices: Can they be used to improve national house price forecasts? *Bank of England Quarterly Bulletin*, 304-314.

Woodworth, M. D., & Wallace, J. L. (2017). Seeing ghosts: Parsing China's "ghost city" controversy. *Urban Geography, 38*(8), 1270-1281.

Wu, D. M., Guo, Z. X., & Chen, H. G. (2008). The impact of lake ecological landscape in urban residential area on housing price: a case study on the Mo Chou Lake, Nanjing. *Resource Science, 30*(10), 1503-1510.

Wu, J., Gyourko, J., & Deng, Y. (2012). Evaluating conditions in major Chinese housing markets. *Regional Science and Urban Economics, 42*, 531-543.

Xu, X. H. (1997). An analysis on the spatial distribution characters of commercial residence price in shanghai. *Economic Geography, 17*(1), 80-87. (in Chinese)

Yamazaki, R. (2001). Empirical Testing of real option pricing models using land price index in Japan. *Journal of Property Investment and Finance, 19*(1), 53-72.

Yang, J., Bao, Y., Zhang, Y., Li, X., & Ge, Q. (2018). Impact of Accessibility on House prices in Dalian City of China Based on a Geographically Weighted Regression Model. *Chinese Geographical Science, 28*(3), 505-515.

Yang, L., Zhou, J., & Shyr, O. F. (2019). Does bus accessibility affect property prices? *Cities, 84*, 56-65.

Yang, T. C., Noah, A. J., & Shoff, C. (2015). Exploring geographic variation in US mortality rates using a spatial durbin approach. *Population, Space and Place, 21*(1), 18-37.

Yang, X., Wu, Y., Shen, Q., & Dang, H. (2017). Measuring the degree of speculation in the residential housing market: A spatial econometric model and its application in China. *Habitat International, 67*, 96-104.

Yao, H., & Pretorius, F. (2004). Empirical Testing of Real Options in the Hong Kong Residential Real Estate Market.

Yao, J. (2014). An investigation into the impact of movable solar shades on energy, indoor thermal and visual comfort improvements. *Building and Environment, 71*, 24-32.

Yu, H. (2010). China's house price: affected by economic fundamentals or real estate policy. *Frontiers of Economics in China, 5*(1), 25-51.

Yu, K. H., & Hui, E. C. M. (2018). Housing construction and uncertainties in a high-rise city. *Habitat International*.

Yu, W., Ai, T., & Shao, S. (2015). The analysis and delimitation of Central Business District using network kernel density estimation. *Journal of Transport Geography, 45*, 32-47.

Yu, W., Sheblé, G.B., Lopes, J. A. P., & Matos, M. A. (2006). Valuation of switchable tariff for wind energy. *Electric Power Systems Research, 76*(5), 382-388.

Zeng, H., Yu, X., & Wen, H. (2017). What factors drive public rental housing fraud? Evidence from Hangzhou, China. *Habitat International, 66*, 57-64.

Zeng, S., & Zhang, S. (2011). Real options literature review. *IBusiness, 3*(1), 43.

Zhang, C., Jia, S., & Yang, R. (2016). Housing affordability and housing vacancy in China: The role of income inequality. *Journal of Housing Economics, 33*(1), 4-14.

Zhang, L., & Yi, Y. (2017). Quantile house price indices in Beijing. *Regional Science and Urban Economics, 63*(1), 85-96.

Zhang, L., & Yi, Y. (2018). What contributes to the rising house prices in Beijing? A decomposition approach. *Journal of Housing Economics, 41*(1), 72-84.

Zhang, L., Hui, E. C., & Wen, H. (2017). The regional house prices in China: Ripple effect or differentiation. *Habitat International, 67*(1), 118-128.

Zhang, S. J., Shao, L. G., & Wang, G. S. (2015). Analysis of House Price Spillover Effect - Evidence from the Yangtze River Delta Economic Zone in China. *Metallurgical & Mining Industry, 2*, 96-104.

Zhang, X., Geltner, D., & de Neufville, R. (2018). System Dynamics Modeling of Chinese Urban Housing Markets for Pedagogical and Policy Analysis Purposes. *Journal of Real Estate Finance and Economics, 57*(3), 476-501.

Zhong, H. Y., Zhang, A. L., & Cai, Y. Y. (2009). The impact of the South Lake landscape in Wuhan on housing price: an empirical study based on the hedonic model. *Land Science of China, 23*(12), 63-68.

Appendix

This Appendix contains two sections, which are Appendix A and Appendix B. Appendix A provides the relative tables of the empirical chapters (Chapter 4, Chapter 5 and Chapter 6). And, Appendix B provides the relative figures of the empirical chapters (Chapter 4, Chapter 5 and Chapter 6).

Appendix A

Table A.1 – Table A.87 are belonging to **Chapter 4 An Empirical Analysis of the Effect of Housing Characteristics on Property Price in Beijing**

Table A.1: Variable List

Name	Variables
P	House price times
AS	House size
FR	Floor level of house
BR	Number of bedrooms
LR	Number of living rooms
HPP	House planning permissions
HCP	House completed permissions
HPI	House price index
MR	Mortgage payment rates
UR	Unemployment rates
IC	Income
IR	Central bank interest rate
CPI	Consumer price index
GRP	Gross regional product
IFA	Total investment in fixed assets
GR	Local governments general budgetary revenue
GE	Local governments general budgetary expenditure
VC	Gross output value of construction
MS	Money supply
S	South
N	North
E	East
W	West
SE	Southeast
SW	Southwest
NE	Northeast
NW	Northwest
NS	North and south
WE	West and east
Region_ID 1	Dongcheng district
Region_ID 2	Xicheng district
Region_ID 3	Chongwen district
Region_ID 4	Xuanwu district
Region_ID 5	Chaoyang district
Region_ID 6	Fengtai district
Region_ID 7	Haidian district

Notes: All variables were downloaded from the Soufang DataStream and the Beijing municipal commission on house and urban-rural development website. Data is from 2/1/2002 to 11/18/2014.

Table A.2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
House Price	17,143	36.87	24.74	0.27	937.5
Size	17,143	122.9	64.13	16.36	656
Floor_level	17,143	19.51	9.24	1	66
Bedroom_nums	17,143	2.22	0.96	1	8
Livingroom_nums	17,143	1.47	0.64	0	4
House_planning_permissions	17,143	4.07	0.07	3.88	4.14
House_completed_permissions	17,143	3.44	0.05	3.35	3.58
House_price_index	17,143	109.8	7.08	97.4	122
Mortgage_ payment_rate	17,143	0.07	0.00	0.058	0.078
Unemployment_rate	17,143	0.01	0.00	0.012	0.021
Income	17,143	4.73	0.16	4.32	4.89
Central_bank_interest_rate	17,143	0.06	0.005	0.053	0.075
Consumer Price Index	17,143	102.2	1.76	98.2	105.6
Gross Regional Product	17,143	4.14	0.21	3.63	4.33
Total Investment in Fixed Assets in the Whole Country	17,143	3.70	0.17	3.25	3.84
Local Governments General Budgetary Revenue	17,143	3.37	0.27	2.73	3.60
Local Governments General Budgetary Expenditure	17,143	3.42	0.26	2.80	3.66
Gross Output Value of Construction	17,143	3.67	0.27	3.02	3.91
Money Supply	17,143	5.82	0.26	5.20	6.08
South	17,143	0.14	0.35	0	1
North	17,143	0.07	0.26	0	1
East	17,143	0.10	0.29	0	1
West	17,143	0.07	0.26	0	1
Southeast	17,143	0.11	0.31	0	1
Southwest	17,143	0.08	0.27	0	1
Northeast	17,143	0.05	0.21	0	1
North & South	17,143	0.32	0.47	0	1
West & East	17,143	0.03	0.17	0	1
Region_ID	17,143	4.78	1.40	1	7
Year	17,143	2010	3.7	2002	2014

Notes: This table summarises descriptive statistics (number of observations, sample mean, standard deviation, minimum and maximum) of the full sample of variables.

Table A.3: Results of Breusch-Pagan Test for Heteroskedasticity in OLS Estimator

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
AS	0.05	0.00	13.9	0	0.0463	0.0615
FR	22.94	2.55	8.99	0	17.9348	27.9402
FR2	-0.33	0.06	-5.94	0	-0.4440	-0.2237
BR	-2.09	0.27	-7.65	0	-2.6276	-1.5556
LRFR	-0.14	0.02	-5.81	0	-0.1861	-0.0923
LR	2.92	0.56	5.22	0	1.8220	4.0112
HPP	120.81	8.14	14.85	0	104.8616	136.7536
FRHPP	-5.74	0.63	-9.16	0	-6.9686	-4.5114
FR2HPP	0.09	0.01	6.2	0	0.0586	0.1127
HPI	0.20	0.02	9.48	0	0.1598	0.2431
MR	-292.38	30.45	-9.6	0	-352.0614	-232.6909
IC	77.15	2.17	35.54	0	72.8923	81.4022
NS	2.22	0.37	5.99	0	1.4931	2.9464
_cons	-824.27	29.00	-28.42	0	-881.1117	-767.4218
Breusch-Pagan test	chi2(1) = 9.68					
	Prob > chi2 = 0.0019					

Notes: This table provides results of the Breusch-Pagan test. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.4: Results of Breusch-Godfrey LM Test for Autocorrelation in OLS Estimator

	Coef.	**Std. Err.**	**t**	**P-value**	**[95% Conf. Interval]**	
AS	0.05	0.00	13.9	0	0.0463	0.0615
FR	22.94	2.55	8.99	0	17.9348	27.9402
FR2	-0.33	0.06	-5.94	0	-0.4440	-0.2237
BR	-2.09	0.27	-7.65	0	-2.6276	-1.5556
LRFR	-0.14	0.02	-5.81	0	-0.1861	-0.0923
LR	2.92	0.56	5.22	0	1.8220	4.0112
HPP	120.81	8.14	14.85	0	104.8616	136.7536
FRHPP	-5.74	0.63	-9.16	0	-6.9686	-4.5114
FR2HPP	0.09	0.01	6.2	0	0.0586	0.1127
HPI	0.20	0.02	9.48	0	0.1598	0.2431
MR	-292.38	30.45	-9.6	0	-352.0614	-232.6909
IC	77.15	2.17	35.54	0	72.8923	81.4022
NS	2.22	0.37	5.99	0	1.4931	2.9464
_cons	-824.27	29.00	-28.42	0	-881.1117	-767.4218
Breusch-Godfrey LM test	lags(p) = 1					
	chi2 = 130.612					
	df = 1					
	Prob > chi2 = 0					

Notes: This table provides results of the Breusch-Godfrey LM test. The null hypothesis of Breusch-Godfrey LM is that there is no serial correlation in the model.

Table A.5: Results of Hausman Test in Panel Model

	(b)	**(B)**	**(b-B)**
	Fixed	**Random**	**Difference**
AS	0.0617	0.0548	0.0069
FR	22.4138	21.6995	0.7142
FR2	-0.3036	-0.3161	0.0125
BR	-2.6302	-2.1006	-0.5296
LR	0.4467	0.1644	0.2823
HPP	118.0117	118.2172	-0.2055
FRHPP	-5.5937	-5.4947	-0.0990
FR2HPP	0.0777	0.0815	-0.0038
HPI	0.1931	0.2012	-0.0081
MR	-278.7437	-292.0275	13.2839
IC	79.3844	77.0973	2.2870
NS	2.4784	2.3182	0.1603
Hausman Test	chi2(10) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 679.9		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.6: Results of Wooldridge Test for Autocorrelation in Panel Model

	Coef.	Robust Std. Err.	t	P-value	[95% Conf. Interval]	
AS D1.	0.0658	0.0151	4.36	0.005	0.0289	0.1028
FR D1.	25.3360	12.5309	2.02	0.09	-5.3260	55.9980
FR2 D1.	-0.3630	0.1691	-2.15	0.075	-0.7768	0.0508
BR D1.	-2.9990	0.2742	-10.94	0	-3.6699	-2.3280
LR D1.	0.6317	0.4799	1.32	0.236	-0.5427	1.8061
HPP D1.	122.5829	38.3787	3.19	0.019	28.6735	216.4923
FRHPP D1.	-6.3228	3.1289	-2.02	0.09	-13.9789	1.3333
FR2HPP D1.	0.0924	0.0422	2.19	0.071	-0.0109	0.1956
HPI D1.	0.1710	0.0166	10.31	0	0.1304	0.2116
MR D1.	-281.1627	89.2891	-3.15	0.02	-499.6452	-62.6802
IC D1.	79.3620	7.8734	10.08	0	60.0965	98.6276
NS D1.	2.6498	1.4966	1.77	0.127	-1.0123	6.3119
Wooldridge Test	F(1,6) = 0.669					
	Prob > F = 0.4447					

Notes: This table provides results of the Wooldridge test. The null hypothesis is that there is no first-order autocorrelation in the model.

Table A.7: Results of Likelihood-ratio Test for Groupwise Heteroskedasticity in Panel Model

Cross-sectional time-series FGLS regression						
Coefficients: generalized least squares						
Panels: heteroskedastic						
	Coef.	**Std. Err.**	**z**	**P-value**	**[95% Conf. Interval]**	
AS	0.0621	0.0030	20.48	0	0.0561	0.0680
FR	6.3742	2.1133	3.02	0.003	2.2322	10.5162
FR2	-0.1084	0.0430	-2.52	0.012	-0.1926	-0.0242
BR	-2.5888	0.2228	-11.62	0	-3.0255	-2.1520
LR	-0.0055	0.2376	-0.02	0.982	-0.4711	0.4601
HPP	60.2255	7.2381	8.32	0	46.0390	74.4120
FRHPP	-1.6553	0.5192	-3.19	0.001	-2.6728	-0.6378
FR2HPP	0.0296	0.0106	2.8	0.005	0.0089	0.0503
HPI	0.2046	0.0172	11.89	0	0.1709	0.2383
MR	-232.0307	25.1767	-9.22	0	-281.3761	-182.6854
IC	72.8319	1.7863	40.77	0	69.3308	76.3329
NS	1.8089	0.3025	5.98	0	1.2159	2.4018
_cons	-562.6226	26.5223	-21.21	0	-614.6055	-510.6398

Panels: homoskedastic						
	Coef.	**Std. Err.**	**z**	**P-value**	**[95% Conf. Interval]**	
AS	0.0548	0.0039	14.14	0	0.0472	0.0624
FR	21.6995	2.5448	8.53	0	16.7118	26.6873
FR2	-0.3161	0.0561	-5.63	0	-0.4261	-0.2060
BR	-2.1006	0.2736	-7.68	0	-2.6369	-1.5643
LR	0.1644	0.2966	0.55	0.579	-0.4169	0.7456
HPP	118.2172	8.1278	14.54	0	102.2871	134.1473
FRHPP	-5.4947	0.6257	-8.78	0	-6.7212	-4.2683
FR2HPP	0.0815	0.0138	5.9	0	0.0544	0.1085
HPI	0.2012	0.0213	9.46	0	0.1596	0.2429
MR	-292.0275	30.4676	-9.58	0	-351.7430	-232.3121
IC	77.0973	2.1720	35.5	0	72.8402	81.3544
NS	2.3182	0.3705	6.26	0	1.5919	3.0444
_cons	-809.2254	28.9021	-28	0	-865.8725	-752.5782
Likelihood-ratio Test	LR chi2(6) = 3999.35					
	Prob > chi2 = 0.00					

Notes: This table provides results of the Likelihood-ratio test. The null hypothesis is that homoscedastic is nested in heteroskedastic.

Table A.8: Results of Friedman's Test for Cross-sectional Correlation in Panel Model

	Coef.	**Std. Err.**	**t**	**P-value**	**[95% Conf. Interval]**	
AS	0.0617	0.0037	16.58	0	0.0544	0.0690
FR	22.4138	2.4133	9.29	0	17.6834	27.1441
FR2	-0.3036	0.0531	-5.72	0	-0.4076	-0.1996
BR	-2.6302	0.2611	-10.08	0	-3.1419	-2.1185
LR	0.4467	0.2800	1.6	0.111	-0.1021	0.9955
HPP	118.0117	7.7089	15.31	0	102.9014	133.1220
FRHPP	-5.5937	0.5931	-9.43	0	-6.7562	-4.4312
FR2HPP	0.0777	0.0130	5.95	0	0.0521	0.1032
HPI	0.1931	0.0201	9.62	0	0.1538	0.2325
MR	-278.7437	28.7429	-9.7	0	-335.0826	-222.4047
IC	79.3844	2.0515	38.7	0	75.3633	83.4054
NS	2.4784	0.3538	7.01	0	1.7850	3.1719
_cons	-823.9214	27.4906	-29.97	0	-877.8057	-770.0370
Friedman's Test	Cross sectional independence = 264.505					
	Pr = 0.00					

Notes: This table provides results of the Friedman's test. The null hypothesis is there is no cross-sectional correlation in the model.

Table A.9: Results of First Stage Regression for GMM (MR as endogenous variables, IR and CPI as instruments)

MR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	3.36E-07	1.29E-07	2.6	0.009	8.31E-08	5.89E-07
FR	8.62E-05	8.25E-05	1.04	0.296	-7.55E-05	2.48E-04
FR2	-1.09E-06	1.74E-06	-0.62	0.533	-4.51E-06	2.33E-06
BR	-1.67E-05	9.23E-06	-1.81	0.071	-3.48E-05	1.41E-06
LR	-1.32E-06	9.30E-06	-0.14	0.887	-1.95E-05	1.69E-05
HPP	-3.62E-03	2.79E-04	-12.97	0	-4.17E-03	-3.08E-03
FRHPP	-2.21E-05	2.00E-05	-1.1	0.27	-6.13E-05	1.72E-05
FR2HPP	2.80E-07	4.23E-07	0.66	0.508	-5.49E-07	1.11E-06
HPI	6.61E-06	4.42E-07	14.96	0	5.75E-06	7.48E-06
IC	3.08E-03	7.41E-05	41.6	0	2.94E-03	3.23E-03
NS	-2.40E-05	1.16E-05	-2.06	0.039	-4.68E-05	-1.17E-06
IR	0.9521	0.0019003	501.06	0	9.48E-01	9.56E-01
CPI	-3.99E-05	5.23E-06	-7.63	0	-5.02E-05	-2.96E-05
_cons	1.19E-02	9.60E-04	12.38	0	1.00E-02	1.38E-02

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.10: Results of Hausman Test for GMM (MR as endogenous variable, IR and CPI as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**ols**	**Difference**
MR	-254.4061	-292.0275	37.6214
AS	0.0548	0.0548	-0.0001
FR	21.6922	21.6995	-0.0073
FR2	-0.3164	-0.3161	-0.0003
BR	-2.1011	-2.1006	-0.0005
LR	0.1647	0.1644	0.0003
HPP	118.2787	118.2172	0.0615
FRHPP	-5.4926	-5.4947	0.0021
FR2HPP	0.0816	0.0815	0.0001
HPI	0.1996	0.2012	-0.0016
IC	76.7025	77.0973	-0.3948
NS	2.3266	2.3182	0.0084
_cons	-809.8862	-809.2254	-0.6608
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 91.26		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.11: Results of Sargan Test for GMM (MR as endogenous variable, IR and CPI as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-254.4061	30.7223	-8.28	0	-314.6206	-194.1916
AS	0.0548	0.0039	14.12	0	0.0472	0.0624
FR	21.6922	2.5449	8.52	0	16.7042	26.6802
FR2	-0.3164	0.0561	-5.63	0	-0.4264	-0.2063
BR	-2.1011	0.2736	-7.68	0	-2.6374	-1.5648
LR	0.1647	0.2966	0.56	0.579	-0.4166	0.7459
HPP	118.2787	8.1281	14.55	0	102.3478	134.2095
FRHPP	-5.4926	0.6258	-8.78	0	-6.7191	-4.2661
FR2HPP	0.0816	0.0138	5.91	0	0.0545	0.1086
HPI	0.1996	0.0213	9.39	0	0.1579	0.2413
IC	76.7025	2.1725	35.31	0	72.4444	80.9605
NS	2.3266	0.3706	6.28	0	1.6003	3.0529
_cons	-809.8862	28.9035	-28.02	0	-866.5360	-753.2364
Sargan Test	chi2(1) = 0.237623					
	p = 0.6259					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.12: Results of Endogenous Test for GMM (MR as endogenous variable, IR and CPI as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
MR	0.9853	0.9853	0.9836	513003	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
MR	0.9836		0.9836		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	19.93		11.59	8.75	7.25

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.13: Results of Hausman Test for GMM in Panel Model (MR as endogenous variable, IR and CPI as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
MR	-244.3859	-278.7437	34.3578
AS	0.0617	0.0617	-0.0001
FR	22.3992	22.4138	-0.0145
FR2	-0.3038	-0.3036	-0.0002
BR	-2.6301	-2.6302	0.0000
LR	0.4473	0.4467	0.0006
HPP	118.0459	118.0117	0.0341
FRHPP	-5.5899	-5.5937	0.0037
FR2HPP	0.0777	0.0777	0.0000
HPI	0.1917	0.1931	-0.0015
IC	79.0219	79.3844	-0.3625
NS	2.4878	2.4784	0.0094
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 85.66		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.14: Results of Sargan Test for GMM in Panel Model (MR as endogenous variable, IR and CPI as instruments)

	Coef.	**Std. Err.**	**t**	**P-value**	**[95% Conf. Interval]**	
MR	-244.3859	28.9727	-8.44	0	-301.1713	-187.6005
AS	0.0617	0.0037	16.57	0	0.0544	0.0689
FR	22.3992	2.4126	9.28	0	17.6707	27.1278
FR2	-0.3038	0.0530	-5.73	0	-0.4077	-0.1998
BR	-2.6301	0.2610	-10.08	0	-3.1417	-2.1186
LR	0.4473	0.2799	1.6	0.11	-0.1013	0.9959
HPP	118.0459	7.7066	15.32	0	102.9413	133.1505
FRHPP	-5.5899	0.5929	-9.43	0	-6.7520	-4.4279
FR2HPP	0.0777	0.0130	5.96	0	0.0521	0.1032
HPI	0.1917	0.0201	9.55	0	0.1523	0.2310
IC	79.0219	2.0512	38.52	0	75.0016	83.0421
NS	2.4878	0.3537	7.03	0	1.7946	3.1810
Sargan Test	chi2(1) = 0.026					
	p = 0.8708					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.15: Results of Endogenous Test for GMM in Panel Model (MR as endogenous variable, IR and CPI as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
MR	17000		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	19.93	11.59	8.75	7.25

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.16: Results of First Stage Regression for GMM (MR and IC as endogenous variables, IR, CPI and GRP as instruments)

MR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	3.20E-07	1.28E-07	2.5	0.013	6.88E-08	5.72E-07
FR	7.75E-05	8.31E-05	0.93	0.351	-8.54E-05	2.40E-04
FR2	-8.82E-07	1.74E-06	-0.51	0.612	-4.29E-06	2.53E-06
BR	-1.61E-05	9.18E-06	-1.75	0.08	-3.41E-05	1.93E-06
LR	-7.94E-07	9.24E-06	-0.09	0.932	-1.89E-05	1.73E-05
HPP	-3.12E-03	2.64E-04	-11.78	0	-3.63E-03	-2.60E-03
FRHPP	-1.99E-05	2.02E-05	-0.99	0.325	-5.94E-05	1.97E-05
FR2HPP	2.28E-07	4.22E-07	0.54	0.588	-5.98E-07	1.05E-06
HPI	6.44E-06	4.34E-07	14.83	0	5.59E-06	7.29E-06
NS	-2.30E-05	1.16E-05	-1.99	0.047	-4.58E-05	-3.36E-07
IR	9.56E-01	1.82E-03	525.55	0	9.52E-01	9.59E-01
CPI	-6.54E-05	4.84E-06	-13.5	0	-7.49E-05	-5.59E-05
GRP	2.33E-03	4.88E-05	47.86	0	2.24E-03	2.43E-03
_cons	1.71E-02	9.85E-04	17.37	0	1.52E-02	1.90E-02

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

IC	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	-3.37E-06	2.07E-06	-1.62	0.104	-7.44E-06	6.98E-07
FR	-3.50E-03	1.43E-03	-2.45	0.014	-6.29E-03	-7.01E-04
FR2	8.55E-05	2.96E-05	2.89	0.004	2.75E-05	1.44E-04
BR	-3.71E-05	1.46E-04	-0.25	0.8	-3.24E-04	2.50E-04
LR	2.40E-04	1.54E-04	1.56	0.119	-6.20E-05	5.43E-04
HPP	2.65E-01	4.80E-03	55.19	0	2.56E-01	2.75E-01
FRHPP	8.79E-04	3.48E-04	2.52	0.012	1.96E-04	1.56E-03
FR2HPP	-2.14E-05	7.22E-06	-2.96	0.003	-3.55E-05	-7.20E-06
HPI	-6.59E-06	1.32E-05	-0.5	0.616	-3.24E-05	1.92E-05
NS	3.00E-04	1.92E-04	1.57	0.117	-7.54E-05	6.76E-04
IR	1.32E+00	3.36E-02	39.2	0	1.25E+00	1.38E+00
CPI	-8.39E-03	9.86E-05	-85.1	0	-8.59E-03	-8.20E-03
GRP	7.17E-01	7.69E-04	933.32	0	7.16E-01	7.19E-01
_cons	1.45E+00	1.74E-02	83.78	0	1.42E+00	1.49E+00

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.17: Results of Hausman Test for GMM (MR and IC as endogenous variables, IR, CPI and GRP as instruments)

	(b)	(B)	(b-B)
	iv	**ols**	**Difference**
MR	-260.3290	-292.0275	31.6985
IC	80.6708	77.0973	3.5735
AS	0.0547	0.0548	-0.0002
FR	21.7845	21.6995	0.0850
FR2	-0.3186	-0.3161	-0.0026
BR	-2.0856	-2.1006	0.0150
LR	0.1596	0.1644	-0.0048
HPP	110.4212	118.2172	-7.7960
FRHPP	-5.5156	-5.4947	-0.0209
FR2HPP	0.0821	0.0815	0.0006
HPI	0.1979	0.2012	-0.0033
NS	2.3244	2.3182	0.0062
_cons	-796.0722	-809.2254	13.1532
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 274		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.18: Results of Sargan Test for GMM (MR and IC as endogenous variables, IR, CPI and GRP as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-260.3290	30.7363	-8.47	0	-320.5709	-200.0871
IC	80.6708	2.1975	36.71	0	76.3638	84.9777
AS	0.0547	0.0039	14.1	0	0.0471	0.0623
FR	21.7845	2.5452	8.56	0	16.7961	26.7729
FR2	-0.3186	0.0562	-5.67	0	-0.4287	-0.2086
BR	-2.0856	0.2737	-7.62	0	-2.6219	-1.5492
LR	0.1596	0.2966	0.54	0.591	-0.4217	0.7409
HPP	110.4212	8.1542	13.54	0	94.4393	126.4030
FRHPP	-5.5156	0.6258	-8.81	0	-6.7422	-4.2890
FR2HPP	0.0821	0.0138	5.95	0	0.0551	0.1092
HPI	0.1979	0.0213	9.31	0	0.1562	0.2396
NS	2.3244	0.3706	6.27	0	1.5980	3.0507
_cons	-796.0722	28.9283	-27.52	0	-852.7705	-739.3739
Sargan Test	chi2(1) = 0.016395					
	p = 0.8981					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous)

Table A.19: Results of Endogenous Test for GMM (MR and IC as endogenous variables, IR, CPI and GRP as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(3,17129)	Prob > F
MR	0.9854	0.9854	0.9841	353266	0
IC	0.9964	0.9964	0.9784	259215	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
MR	0.9828		0.9828		
IC	0.9772		0.9772		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	13.43		8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.20: Results of Hausman Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GRP as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
MR	-250.3979	-278.7437	28.3457
IC	83.0350	79.3844	3.6506
AS	0.0616	0.0617	-0.0001
FR	22.5012	22.4138	0.0874
FR2	-0.3062	-0.3036	-0.0026
BR	-2.6185	-2.6302	0.0117
LR	0.4422	0.4467	-0.0045
HPP	110.1347	118.0117	-7.8770
FRHPP	-5.6150	-5.5937	-0.0213
FR2HPP	0.0783	0.0777	0.0006
HPI	0.1899	0.1931	-0.0032
NS	2.4856	2.4784	0.0072
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 291.5		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.21: Results of Sargan Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GRP as instruments)

	Coef.	**Std. Err.**	**t**	**P-value**	**[95% Conf. Interval]**	
MR	-250.3979	28.9864	-8.64	0	-307.2102	-193.5856
IC	83.0350	2.0749	40.02	0	78.9683	87.1016
AS	0.0616	0.0037	16.56	0	0.0543	0.0689
FR	22.5012	2.4128	9.33	0	17.7722	27.2303
FR2	-0.3062	0.0531	-5.77	0	-0.4102	-0.2022
BR	-2.6185	0.2610	-10.03	0	-3.1301	-2.1070
LR	0.4422	0.2799	1.58	0.114	-0.1064	0.9909
HPP	110.1347	7.7310	14.25	0	94.9823	125.2872
FRHPP	-5.6150	0.5930	-9.47	0	-6.7772	-4.4529
FR2HPP	0.0783	0.0130	6	0	0.0527	0.1038
HPI	0.1899	0.0201	9.46	0	0.1506	0.2292
NS	2.4856	0.3537	7.03	0	1.7923	3.1789
Sargan Test	chi2(1) = 0.298					
	p = 0.5851					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.22: Results of Endogenous Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GRP as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
MR IC	17000		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	13.43	8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.23: Results of First Stage Regression for GMM (MR and IC as endogenous variables, IR, CPI and IFA as instruments)

MR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	2.59E-07	1.23E-07	2.1	0.036	1.72E-08	5.01E-07
FR	7.25E-05	7.76E-05	0.93	0.35	-7.96E-05	2.25E-04
FR2	-9.23E-07	1.64E-06	-0.56	0.574	-4.14E-06	2.29E-06
BR	-1.14E-05	8.85E-06	-1.29	0.196	-2.88E-05	5.91E-06
LR	-1.35E-06	8.87E-06	-0.15	0.879	-1.87E-05	1.60E-05
HPP	-4.53E-03	2.36E-04	-19.16	0	-4.99E-03	-4.06E-03
FRHPP	-1.85E-05	1.88E-05	-0.98	0.325	-5.54E-05	1.84E-05
FR2HPP	2.37E-07	3.98E-07	0.6	0.552	-5.43E-07	1.02E-06
HPI	3.30E-06	4.25E-07	7.77	0	2.47E-06	4.13E-06
NS	-2.06E-05	1.11E-05	-1.85	0.064	-4.24E-05	1.22E-06
IR	9.59E-01	1.72E-03	558.66	0	9.56E-01	9.63E-01
CPI	-6.54E-05	4.76E-06	-13.75	0	-7.47E-05	-5.61E-05
IFA	3.50E-03	4.83E-05	72.58	0	3.41E-03	3.60E-03
_cons	1.97E-02	9.11E-04	21.62	0	1.79E-02	2.15E-02

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

IC	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	-1.07E-05	3.90E-06	-2.74	0.006	-1.83E-05	-3.03E-06
FR	-7.44E-03	2.28E-03	-3.26	0.001	-1.19E-02	-2.97E-03
FR2	1.53E-04	5.25E-05	2.91	0.004	4.96E-05	2.56E-04
BR	8.76E-05	2.77E-04	0.32	0.752	-4.55E-04	6.30E-04
LR	3.92E-04	2.91E-04	1.35	0.178	-1.78E-04	9.62E-04
HPP	3.42E-01	7.00E-03	48.93	0	3.29E-01	3.56E-01
FRHPP	1.88E-03	5.56E-04	3.38	0.001	7.89E-04	2.97E-03
FR2HPP	-3.83E-05	1.28E-05	-3	0.003	-6.34E-05	-1.32E-05
HPI	-5.48E-04	2.34E-05	-23.38	0	-5.94E-04	-5.02E-04
NS	8.40E-04	3.57E-04	2.35	0.019	1.40E-04	1.54E-03
IR	2.65E+00	7.20E-02	36.84	0	2.51E+00	2.79E+00
CPI	-8.92E-03	1.88E-04	-47.48	0	-9.29E-03	-8.55E-03
IFA	8.31E-01	1.03E-03	803.92	0	8.29E-01	8.33E-01
_cons	1.07E+00	2.51E-02	42.65	0	1.02E+00	1.12E+00

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.24: Results of Hausman Test for GMM (MR and IC as endogenous variables, IR, CPI and IFA as instruments)

	(b)	(B)	(b-B)
	iv	**ols**	**Difference**
MR	-256.8723	-292.0275	35.1552
IC	78.3343	77.0973	1.2370
AS	0.0547	0.0548	-0.0001
FR	21.7301	21.6995	0.0306
FR2	-0.3173	-0.3161	-0.0012
BR	-2.0947	-2.1006	0.0059
LR	0.1626	0.1644	-0.0018
HPP	115.0482	118.2172	-3.1690
FRHPP	-5.5021	-5.4947	-0.0074
FR2HPP	0.0818	0.0815	0.0003
HPI	0.1989	0.2012	-0.0023
NS	2.3257	2.3182	0.0075
_cons	-804.2063	-809.2254	5.0190
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 143.78		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.25: Results of Sargan Test for GMM (MR and IC as endogenous variables, IR, CPI and IFA as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-255.9604	18.0773	-14.16	0	-291.3913	-220.5295
IC	78.2351	1.3671	57.23	0	75.5557	80.9145
AS	0.0549	0.0042	13.05	0	0.0467	0.0632
FR	21.6540	2.6395	8.2	0	16.4807	26.8274
FR2	-0.3162	0.0472	-6.7	0	-0.4087	-0.2236
BR	-2.0944	0.2539	-8.25	0	-2.5921	-1.5967
LR	0.1481	0.3023	0.49	0.624	-0.4445	0.7407
HPP	114.7670	9.3310	12.3	0	96.4786	133.0554
FRHPP	-5.4827	0.6584	-8.33	0	-6.7731	-4.1923
FR2HPP	0.0815	0.0117	6.94	0	0.0585	0.1045
HPI	0.2009	0.0229	8.77	0	0.1560	0.2458
NS	2.3300	0.4918	4.74	0	1.3661	3.2939
_cons	-802.9208	36.0580	-22.27	0	-873.5932	-732.2484
Sargan Test	chi2(1) = 0.115754					
	p = 0.7337					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.26: Results of Endogenous Test for GMM (MR and IC as endogenous variables, IR, CPI and IFA as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
MR	0.9864	0.9864	0.9852	380600	0
IC	0.9873	0.9873	0.924	69457.6	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
MR	0.9795		0.9795		
IC	0.9187		0.9187		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	13.43		8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.27: Results of Hausman Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and IFA as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
MR	-247.4559	-278.7437	31.2878
IC	81.0895	79.3844	1.7052
AS	0.0616	0.0617	-0.0001
FR	22.4518	22.4138	0.0380
FR2	-0.3050	-0.3036	-0.0014
BR	-2.6242	-2.6302	0.0060
LR	0.4447	0.4467	-0.0020
HPP	113.9693	118.0117	-4.0424
FRHPP	-5.6029	-5.5937	-0.0092
FR2HPP	0.0780	0.0777	0.0003
HPI	0.1908	0.1931	-0.0024
NS	2.4867	2.4784	0.0082
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 151.4		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.28: Results of Sargan Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and IFA as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-247.4559	29.0344	-8.52	0	-304.3623	-190.5495
IC	81.0895	2.1399	37.89	0	76.8954	85.2836
AS	0.0616	0.0037	16.56	0	0.0544	0.0689
FR	22.4518	2.4127	9.31	0	17.7230	27.1805
FR2	-0.3050	0.0531	-5.75	0	-0.4090	-0.2010
BR	-2.6242	0.2610	-10.05	0	-3.1357	-2.1126
LR	0.4447	0.2799	1.59	0.112	-0.1039	0.9933
HPP	113.9693	7.7952	14.62	0	98.6909	129.2477
FRHPP	-5.6029	0.5929	-9.45	0	-6.7650	-4.4408
FR2HPP	0.0780	0.0130	5.98	0	0.0524	0.1036
HPI	0.1908	0.0201	9.51	0	0.1514	0.2301
NS	2.4867	0.3537	7.03	0	1.7934	3.1799
Sargan Test	chi2(1) = 0.13					
	p = 0.7184					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.29: Results of Endogenous Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and IFA as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
MR IC	16000		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	13.43	8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.30: Results of First Stage Regression for GMM (MR and IC as endogenous variables, IR, CPI and MS as instruments)

MR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	3.63E-07	1.32E-07	2.75	0.006	1.04E-07	6.22E-07
FR	7.15E-05	8.69E-05	0.82	0.411	-9.88E-05	2.42E-04
FR2	-5.72E-07	1.79E-06	-0.32	0.749	-4.09E-06	2.94E-06
BR	-2.04E-05	9.42E-06	-2.17	0.03	-3.89E-05	-1.94E-06
LR	-3.07E-08	9.52E-06	0	0.997	-1.87E-05	1.86E-05
HPP	-1.79E-03	2.83E-04	-6.33	0	-2.35E-03	-1.24E-03
FRHPP	-1.84E-05	2.11E-05	-0.87	0.383	-5.97E-05	2.30E-05
FR2HPP	1.52E-07	4.35E-07	0.35	0.728	-7.01E-07	1.00E-06
HPI	7.45E-06	4.47E-07	16.68	0	6.58E-06	8.33E-06
NS	-2.44E-05	1.19E-05	-2.04	0.041	-4.78E-05	-1.00E-06
IR	9.61E-01	1.80E-03	533.73	0	9.58E-01	9.65E-01
CPI	-6.20E-05	5.02E-06	-12.34	0	-7.18E-05	-5.21E-05
MS	1.38E-03	4.26E-05	32.28	0	1.29E-03	1.46E-03
_cons	1.26E-02	1.06E-03	11.95	0	1.05E-02	1.47E-02

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

IC	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	3.53E-06	3.78E-06	0.93	0.351	-3.88E-06	1.09E-05
FR	-1.99E-03	3.04E-03	-0.65	0.514	-7.96E-03	3.98E-03
FR2	1.03E-04	5.90E-05	1.74	0.082	-1.30E-05	2.18E-04
BR	-4.21E-04	2.68E-04	-1.57	0.116	-9.46E-04	1.05E-04
LR	1.49E-04	2.85E-04	0.52	0.602	-4.10E-04	7.07E-04
HPP	2.19E-01	1.01E-02	21.58	0	1.99E-01	2.39E-01
FRHPP	5.05E-04	7.43E-04	0.68	0.497	-9.52E-04	1.96E-03
FR2HPP	-2.55E-05	1.44E-05	-1.77	0.076	-5.38E-05	2.69E-06
HPI	1.16E-04	1.98E-05	5.86	0	7.72E-05	1.55E-04
NS	-2.02E-04	3.57E-04	-0.57	0.572	-9.00E-04	4.97E-04
IR	2.76E+00	4.43E-02	62.39	0	2.68E+00	2.85E+00
CPI	-6.27E-03	1.52E-04	-41.28	0	-6.57E-03	-5.97E-03
MS	5.60E-01	1.33E-03	421.05	0	5.57E-01	5.63E-01
_cons	1.04E+00	3.94E-02	26.34	0	9.60E-01	1.11E+00

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.31: Results of Hausman Test for GMM (MR and IC as endogenous variables, IR, CPI and MS as instruments)

	(b)	(B)	(b-B)
	iv	ols	Difference
MR	-272.0238	-292.0275	20.0037
IC	88.4901	77.0973	11.3928
AS	0.0545	0.0548	-0.0003
FR	21.9665	21.6995	0.2669
FR2	-0.3231	-0.3161	-0.0070
BR	-2.0550	-2.1006	0.0456
LR	0.1496	0.1644	-0.0148
HPP	94.9388	118.2172	-23.2784
FRHPP	-5.5609	-5.4947	-0.0662
FR2HPP	0.0832	0.0815	0.0017
HPI	0.1946	0.2012	-0.0067
NS	2.3200	2.3182	0.0019
_cons	-768.8527	-809.2254	40.3726
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 398.58		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.32: Results of Sargan Test for GMM (MR and IC as endogenous variables, IR, CPI and MS as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-273.6937	18.1744	-15.06	0	-309.3148	-238.0726
IC	88.7529	1.4257	62.25	0	85.9586	91.5473
AS	0.0541	0.0042	12.84	0	0.0459	0.0624
FR	22.1046	2.6364	8.38	0	16.9374	27.2718
FR2	-0.3252	0.0469	-6.93	0	-0.4172	-0.2332
BR	-2.0560	0.2543	-8.09	0	-2.5544	-1.5576
LR	0.1738	0.3027	0.57	0.566	-0.4195	0.7671
HPP	95.2434	9.3612	10.17	0	76.8958	113.5909
FRHPP	-5.5960	0.6577	-8.51	0	-6.8850	-4.3070
FR2HPP	0.0838	0.0117	7.17	0	0.0609	0.1066
HPI	0.1912	0.0230	8.31	0	0.1461	0.2363
NS	2.3115	0.4919	4.7	0	1.3474	3.2757
_cons	-770.7655	36.1099	-21.35	0	-841.5395	-699.9915
Sargan Test	chi2(1) = 0.337216					
	p = 0.5614					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.33: Results of Endogenous Test for GMM (MR and IC as endogenous variables, IR, CPI and MS as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
MR	0.9846	0.9846	0.9832	334158	0
IC	0.9879	0.9879	0.9274	72923.6	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
MR	0.9845		0.9845		
IC	0.9286		0.9286		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	13.43		8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.34: Results of Hausman Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and MS as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
MR	-261.8301	-278.7437	16.9135
IC	90.6120	79.3844	11.2276
AS	0.0616	0.0617	-0.0001
FR	22.6937	22.4138	0.2800
FR2	-0.3107	-0.3036	-0.0071
BR	-2.5966	-2.6302	0.0336
LR	0.4327	0.4467	-0.0140
HPP	95.1995	118.0117	-22.8122
FRHPP	-5.6624	-5.5937	-0.0687
FR2HPP	0.0794	0.0777	0.0018
HPI	0.1866	0.1931	-0.0065
NS	2.4814	2.4784	0.0030
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 424.58		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.35: Results of Sargan Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and MS as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-261.8301	28.9853	-9.03	0	-318.6402	-205.0200
IC	90.6120	2.1302	42.54	0	86.4368	94.7872
AS	0.0616	0.0037	16.54	0	0.0543	0.0689
FR	22.6937	2.4148	9.4	0	17.9609	27.4266
FR2	-0.3107	0.0531	-5.85	0	-0.4148	-0.2067
BR	-2.5966	0.2612	-9.94	0	-3.1086	-2.0846
LR	0.4327	0.2801	1.54	0.122	-0.1164	0.9818
HPP	95.1995	7.7969	12.21	0	79.9179	110.4812
FRHPP	-5.6624	0.5934	-9.54	0	-6.8255	-4.4993
FR2HPP	0.0794	0.0131	6.08	0	0.0538	0.1050
HPI	0.1866	0.0201	9.29	0	0.1472	0.2260
NS	2.4814	0.3540	7.01	0	1.7876	3.1753
Sargan Test	chi2(1) = 1.612					
	p = 0.2042					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.36: Results of Endogenous Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and MS as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
MR IC	16000		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	13.43	8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.37: Results of First Stage Regression for GMM (MR and IC as endogenous variables, IR, CPI and GR as instruments)

MR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	3.25E-07	1.29E-07	2.52	0.012	7.20E-08	5.77E-07
FR	7.40E-05	8.42E-05	0.88	0.38	-9.12E-05	2.39E-04
FR2	-7.87E-07	1.76E-06	-0.45	0.654	-4.23E-06	2.65E-06
BR	-1.66E-05	9.21E-06	-1.8	0.071	-3.47E-05	1.43E-06
LR	-4.42E-07	9.29E-06	-0.05	0.962	-1.86E-05	1.78E-05
HPP	-2.48E-03	2.66E-04	-9.33	0	-3.00E-03	-1.96E-03
FRHPP	-1.90E-05	2.04E-05	-0.93	0.353	-5.91E-05	2.11E-05
FR2HPP	2.04E-07	4.26E-07	0.48	0.631	-6.30E-07	1.04E-06
HPI	7.37E-06	4.33E-07	17.03	0	6.52E-06	8.22E-06
NS	-2.30E-05	1.16E-05	-1.98	0.048	-4.58E-05	-1.74E-07
IR	9.55E-01	1.83E-03	520.63	0	9.52E-01	9.59E-01
CPI	-6.94E-05	4.82E-06	-14.4	0	-7.88E-05	-5.99E-05
GR	1.63E-03	3.63E-05	44.75	0	1.55E-03	1.70E-03
_cons	1.91E-02	1.01E-03	18.85	0	1.71E-02	2.11E-02

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

IC	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	-2.97E-06	2.33E-06	-1.27	0.203	-7.55E-06	1.60E-06
FR	-4.23E-03	1.87E-03	-2.27	0.023	-7.90E-03	-5.72E-04
FR2	1.06E-04	3.61E-05	2.93	0.003	3.49E-05	1.77E-04
BR	-8.73E-05	1.65E-04	-0.53	0.596	-4.10E-04	2.35E-04
LR	3.15E-04	1.76E-04	1.78	0.074	-3.11E-05	6.61E-04
HPP	4.12E-01	6.11E-03	67.45	0	4.00E-01	4.24E-01
FRHPP	1.06E-03	4.57E-04	2.33	0.02	1.67E-04	1.96E-03
FR2HPP	-2.64E-05	8.84E-06	-2.99	0.003	-4.37E-05	-9.08E-06
HPI	2.61E-04	1.48E-05	17.68	0	2.32E-04	2.90E-04
NS	3.28E-04	2.19E-04	1.5	0.134	-1.01E-04	7.57E-04
IR	1.03E+00	3.22E-02	32.05	0	9.68E-01	1.09E+00
CPI	-9.60E-03	1.02E-04	-94.34	0	-9.79E-03	-9.40E-03
GR	5.14E-01	5.43E-04	946.62	0	5.13E-01	5.15E-01
_cons	2.21E+00	2.40E-02	92.07	0	2.16E+00	2.25E+00

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.38: Results of Hausman Test for GMM (MR and IC as endogenous variables, IR, CPI and GR as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**ols**	**Difference**
MR	-262.3725	-292.0275	29.6550
IC	82.0415	77.0973	4.9442
AS	0.0546	0.0548	-0.0002
FR	21.8164	21.6995	0.1169
FR2	-0.3194	-0.3161	-0.0033
BR	-2.0802	-2.1006	0.0204
LR	0.1578	0.1644	-0.0065
HPP	107.7069	118.2172	-10.5103
FRHPP	-5.5235	-5.4947	-0.0288
FR2HPP	0.0823	0.0815	0.0008
HPI	0.1973	0.2012	-0.0039
NS	2.3236	2.3182	0.0054
_cons	-791.3003	-809.2254	17.9251
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 313.8		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.39: Results of Sargan Test for GMM (MR and IC as endogenous variables, IR, CPI and GR as instruments)

	Coef.	**Std. Err.**	**t**	**P-value**	**[95% Conf. Interval]**	
MR	-262.3625	18.0687	-14.52	0	-297.7765	-226.9486
IC	82.0400	1.3396	61.24	0	79.4144	84.6656
AS	0.0546	0.0042	12.97	0	0.0464	0.0629
FR	21.8165	2.6374	8.27	0	16.6473	26.9856
FR2	-0.3194	0.0471	-6.78	0	-0.4117	-0.2271
BR	-2.0802	0.2540	-8.19	0	-2.5781	-1.5823
LR	0.1577	0.3025	0.52	0.602	-0.4351	0.7505
HPP	107.7077	9.3513	11.52	0	89.3794	126.0359
FRHPP	-5.5235	0.6579	-8.4	0	-6.8130	-4.2341
FR2HPP	0.0823	0.0117	7.03	0	0.0593	0.1053
HPI	0.1974	0.0229	8.61	0	0.1524	0.2423
NS	2.3236	0.4918	4.72	0	1.3597	3.2876
_cons	-791.2996	36.1123	-21.91	0	-862.0784	-720.5208
Sargan Test	chi2(1) = 0.000015					
	p = 0.9969					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.40: Results of Endogenous Test for GMM (MR and IC as endogenous variables, IR, CPI and GR as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
MR	0.9853	0.9853	0.984	350513	0
IC	0.9953	0.9953	0.9721	199022	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
MR	0.983		0.983		
IC	0.9712		0.9712		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	13.43		8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.41: Results of Hausman Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GR as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
MR	-252.3367	-278.7437	26.4070
IC	84.3255	79.3844	4.9411
AS	0.0616	0.0617	-0.0001
FR	22.5340	22.4138	0.1202
FR2	-0.3070	-0.3036	-0.0034
BR	-2.6148	-2.6302	0.0154
LR	0.4406	0.4467	-0.0061
HPP	107.5909	118.0117	-10.4209
FRHPP	-5.6231	-5.5937	-0.0294
FR2HPP	0.0785	0.0777	0.0008
HPI	0.1893	0.1931	-0.0038
NS	2.4849	2.4784	0.0065
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 330.4		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.42: Results of Sargan Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GR as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-252.3367	28.9858	-8.71	0	-309.1478	-195.5255
IC	84.3255	2.0815	40.51	0	80.2459	88.4050
AS	0.0616	0.0037	16.56	0	0.0543	0.0689
FR	22.5340	2.4130	9.34	0	17.8046	27.2634
FR2	-0.3070	0.0531	-5.79	0	-0.4109	-0.2030
BR	-2.6148	0.2610	-10.02	0	-3.1264	-2.1032
LR	0.4406	0.2799	1.57	0.115	-0.1081	0.9893
HPP	107.5909	7.7387	13.9	0	92.4233	122.7584
FRHPP	-5.6231	0.5930	-9.48	0	-6.7854	-4.4608
FR2HPP	0.0785	0.0130	6.02	0	0.0529	0.1040
HPI	0.1893	0.0201	9.43	0	0.1500	0.2287
NS	2.4849	0.3537	7.02	0	1.7916	3.1782
Sargan Test	chi2(1) = 0.448					
	p = 0.5034					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.43: Results of Endogenous Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GR as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
MR IC	19000		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	13.43	8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.44: Results of First Stage Regression for GMM (MR and IC as endogenous variables, IR, CPI and GE as instruments)

MR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	3.29E-07	1.30E-07	2.54	0.011	7.52E-08	5.83E-07
FR	7.21E-05	8.45E-05	0.85	0.394	-9.36E-05	2.38E-04
FR2	-7.16E-07	1.76E-06	-0.41	0.684	-4.16E-06	2.73E-06
BR	-1.72E-05	9.26E-06	-1.86	0.063	-3.54E-05	9.05E-07
LR	-2.38E-07	9.33E-06	-0.03	0.98	-1.85E-05	1.81E-05
HPP	-2.45E-03	2.68E-04	-9.17	0	-2.98E-03	-1.93E-03
FRHPP	-1.85E-05	2.05E-05	-0.9	0.367	-5.87E-05	2.17E-05
FR2HPP	1.87E-07	4.27E-07	0.44	0.661	-6.50E-07	1.02E-06
HPI	6.80E-06	4.38E-07	15.5	0	5.94E-06	7.65E-06
NS	-2.30E-05	1.17E-05	-1.97	0.049	-4.60E-05	-1.14E-07
IR	9.58E-01	1.82E-03	526.5	0	9.54E-01	9.61E-01
CPI	-6.60E-05	4.88E-06	-13.51	0	-7.56E-05	-5.64E-05
GE	1.63E-03	3.78E-05	43.14	0	1.56E-03	1.70E-03
_cons	1.84E-02	1.02E-03	18.12	0	1.64E-02	2.04E-02

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

IC	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	-2.81E-06	2.58E-06	-1.09	0.276	-7.88E-06	2.25E-06
FR	-4.39E-03	1.90E-03	-2.31	0.021	-8.11E-03	-6.69E-04
FR2	1.16E-04	3.71E-05	3.12	0.002	4.29E-05	1.88E-04
BR	-1.10E-04	1.82E-04	-0.61	0.544	-4.66E-04	2.46E-04
LR	3.32E-04	1.93E-04	1.72	0.086	-4.68E-05	7.11E-04
HPP	3.51E-01	6.31E-03	55.56	0	3.38E-01	3.63E-01
FRHPP	1.10E-03	4.64E-04	2.37	0.018	1.92E-04	2.01E-03
FR2HPP	-2.88E-05	9.08E-06	-3.18	0.002	-4.66E-05	-1.10E-05
HPI	4.52E-05	1.63E-05	2.78	0.005	1.33E-05	7.72E-05
NS	3.15E-04	2.41E-04	1.31	0.19	-1.57E-04	7.86E-04
IR	1.74E+00	3.58E-02	48.58	0	1.67E+00	1.81E+00
CPI	-8.43E-03	1.18E-04	-71.6	0	-8.66E-03	-8.20E-03
GE	5.38E-01	7.25E-04	741.35	0	5.36E-01	5.39E-01
_cons	2.21E+00	2.42E-02	91.46	0	2.16E+00	2.26E+00

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.45: Results of Hausman Test for GMM (MR and IC as endogenous variables, IR, CPI and GE as instruments)

	(b)	(B)	(b-B)
	iv	**ols**	**Difference**
MR	-263.6990	-292.0275	28.3285
IC	82.9304	77.0973	5.8331
AS	0.0546	0.0548	-0.0002
FR	21.8371	21.6995	0.1376
FR2	-0.3199	-0.3161	-0.0039
BR	-2.0767	-2.1006	0.0239
LR	0.1567	0.1644	-0.0077
HPP	105.9469	118.2172	-12.2703
FRHPP	-5.5287	-5.4947	-0.0340
FR2HPP	0.0824	0.0815	0.0010
HPI	0.1970	0.2012	-0.0043
NS	2.3231	2.3182	0.0050
_cons	-788.2061	-809.2254	21.0193
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 316.64		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.46: Results of Sargan Test for GMM (MR and IC as endogenous variables, IR, CPI and GE as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-263.9140	18.0790	-14.6	0	-299.3482	-228.4799
IC	82.9595	1.3418	61.83	0	80.3297	85.5893
AS	0.0546	0.0042	12.96	0	0.0463	0.0628
FR	21.8549	2.6378	8.29	0	16.6849	27.0248
FR2	-0.3202	0.0471	-6.8	0	-0.4125	-0.2279
BR	-2.0768	0.2540	-8.18	0	-2.5747	-1.5790
LR	0.1599	0.3025	0.53	0.597	-0.4329	0.7528
HPP	105.9985	9.3196	11.37	0	87.7324	124.2646
FRHPP	-5.5332	0.6580	-8.41	0	-6.8229	-4.2436
FR2HPP	0.0825	0.0117	7.04	0	0.0595	0.1055
HPI	0.1965	0.0229	8.57	0	0.1516	0.2415
NS	2.3221	0.4918	4.72	0	1.3582	3.2861
_cons	-788.4786	36.0586	-21.87	0	-859.1522	-717.8050
Sargan Test	chi2(1) = 0.005887					
	p = 0.9388					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.47: Results of Endogenous Test for GMM (MR and IC as endogenous variables, IR, CPI and GE as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
MR	0.9852	0.9852	0.9838	347080	0
IC	0.9944	0.9944	0.9664	163986	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
MR	0.9833		0.9833		
IC	0.9659		0.9659		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	13.43		8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.48: Results of Hausman Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GE as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
MR	-253.6978	-278.7437	25.0459
IC	85.2283	79.3844	5.8440
AS	0.0616	0.0617	-0.0001
FR	22.5569	22.4138	0.1432
FR2	-0.3075	-0.3036	-0.0039
BR	-2.6122	-2.6302	0.0180
LR	0.4395	0.4467	-0.0072
HPP	105.8112	118.0117	-12.2005
FRHPP	-5.6288	-5.5937	-0.0351
FR2HPP	0.0786	0.0777	0.0010
HPI	0.1890	0.1931	-0.0042
NS	2.4844	2.4784	0.0060
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 337.6		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.49: Results of Sargan Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GE as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
MR	-253.6978	28.9834	-8.75	0	-310.5042	-196.8914
IC	85.2283	2.0873	40.83	0	81.1372	89.3194
AS	0.0616	0.0037	16.56	0	0.0543	0.0689
FR	22.5569	2.4132	9.35	0	17.8272	27.2867
FR2	-0.3075	0.0531	-5.8	0	-0.4115	-0.2035
BR	-2.6122	0.2610	-10.01	0	-3.1238	-2.1006
LR	0.4395	0.2800	1.57	0.116	-0.1092	0.9882
HPP	105.8112	7.7457	13.66	0	90.6299	120.9926
FRHPP	-5.6288	0.5930	-9.49	0	-6.7911	-4.4664
FR2HPP	0.0786	0.0130	6.03	0	0.0531	0.1042
HPI	0.1890	0.0201	9.41	0	0.1496	0.2283
NS	2.4844	0.3538	7.02	0	1.7910	3.1778
Sargan Test	chi2(1) = 0.571					
	p = 0.45					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.50: Results of Endogenous Test for GMM in Panel Model (MR and IC as endogenous variables, IR, CPI and GE as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
MR IC	16000		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	13.43	8.18	6.4	5.45

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.51: Results of First Stage Regression for GMM (HPP FRHPP and FR2HPP as endogenous variables, IFA GR IFAFR IFAFR2 GRFR and GRFR2 as instruments)

HPP	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	-1.94E-05	5.46E-06	-3.56	0	-3.01E-05	-8.75E-06
FR	-8.34E-03	4.68E-03	-1.78	0.075	-1.75E-02	8.40E-04
FR2	8.45E-05	9.99E-05	0.85	0.398	-1.11E-04	2.80E-04
BR	9.41E-04	3.83E-04	2.46	0.014	1.91E-04	1.69E-03
LR	-3.41E-04	4.03E-04	-0.85	0.396	-1.13E-03	4.48E-04
HPI	-6.14E-05	3.43E-05	-1.79	0.073	-1.29E-04	5.79E-06
MR	1.41E+00	5.03E-02	28.04	0	1.31E+00	1.51E+00
IC	9.26E-01	1.09E-02	84.93	0	9.05E-01	9.48E-01
NS	7.27E-04	5.07E-04	1.44	0.151	-2.66E-04	1.72E-03
IFA	3.97E-01	3.35E-02	11.88	0	3.32E-01	4.63E-01
GR	-5.71E-01	2.12E-02	-26.89	0	-6.13E-01	-5.29E-01
IFAFR	6.06E-03	2.92E-03	2.08	0.038	3.44E-04	1.18E-02
IFAFR2	-7.78E-05	6.17E-05	-1.26	0.207	-1.99E-04	4.31E-05
GRFR	-4.18E-03	1.83E-03	-2.28	0.023	-7.77E-03	-5.86E-04
GRFR2	6.07E-05	3.87E-05	1.57	0.117	-1.51E-05	1.37E-04
_cons	6.11E-02	5.79E-02	1.05	0.292	-5.25E-02	1.75E-01

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

FRHPP	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	-4.60E-04	1.12E-04	-4.13	0	-6.79E-04	-2.42E-04
FR	2.14E+00	2.10E-01	10.16	0	1.72E+00	2.55E+00
FR2	4.88E-03	5.81E-03	0.84	0.401	-6.51E-03	1.63E-02
BR	2.47E-02	7.78E-03	3.17	0.002	9.41E-03	3.99E-02
LR	-7.58E-03	9.05E-03	-0.84	0.402	-2.53E-02	1.02E-02
HPI	-1.03E-03	7.34E-04	-1.4	0.161	-2.47E-03	4.10E-04
MR	2.64E+01	1.10E+00	24	0	2.43E+01	2.86E+01
IC	1.77E+01	2.52E-01	70.21	0	1.72E+01	1.82E+01
NS	1.75E-02	1.04E-02	1.68	0.094	-2.96E-03	3.79E-02
IFA	-3.45E+00	9.46E-01	-3.65	0	-5.30E+00	-1.60E+00
GR	-8.39E+00	6.06E-01	-13.84	0	-9.58E+00	-7.20E+00
IFAFR	7.48E-01	1.28E-01	5.82	0	4.96E-01	9.99E-01
IFAFR2	-3.77E-03	3.55E-03	-1.06	0.289	-1.07E-02	3.19E-03
GRFR	-2.45E-01	8.02E-02	-3.06	0.002	-4.03E-01	-8.83E-02
GRFR2	2.68E-03	2.22E-03	1.21	0.226	-1.66E-03	7.02E-03
_cons	-4.42E+01	1.68E+00	-26.26	0	-4.75E+01	-4.09E+01

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

FR2HPP	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	-1.26E-02	3.38E-03	-3.73	0	-1.92E-02	-5.99E-03
FR	-1.39E+01	1.29E+01	-1.08	0.281	-3.92E+01	1.14E+01
FR2	2.73E+00	3.67E-01	7.44	0	2.01E+00	3.45E+00
BR	6.66E-01	2.12E-01	3.14	0.002	2.50E-01	1.08E+00
LR	-4.08E-02	2.91E-01	-0.14	0.889	-6.12E-01	5.30E-01
HPI	-2.03E-02	2.28E-02	-0.89	0.374	-6.49E-02	2.44E-02
MR	6.17E+02	3.49E+01	17.67	0	5.48E+02	6.85E+02
IC	4.16E+02	8.21E+00	50.69	0	4.00E+02	4.32E+02
NS	5.64E-01	3.12E-01	1.81	0.07	-4.71E-02	1.18E+00
IFA	-1.10E+02	5.31E+01	-2.07	0.039	-2.14E+02	-5.62E+00
GR	-1.81E+02	3.20E+01	-5.66	0	-2.43E+02	-1.18E+02
IFAFR	9.15E+00	7.85E+00	1.17	0.244	-6.24E+00	2.45E+01
IFAFR2	3.34E-01	2.24E-01	1.49	0.136	-1.05E-01	7.73E-01
GRFR	-5.86E+00	4.90E+00	-1.2	0.232	-1.55E+01	3.75E+00
GRFR2	2.97E-02	1.40E-01	0.21	0.832	-2.45E-01	3.04E-01
_cons	-9.92E+02	8.21E+01	-12.09	0	-1.15E+03	-8.31E+02

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.52: Results of Hausman Test for GMM (HPP FRHPP and FR2HPP as endogenous variables, IFA GR IFAFR IFAFR2 GRFR and GRFR2 as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**ols**	**Difference**
HPP	-0.4000	118.2172	-118.6172
FRHPP	-6.4463	-5.4947	-0.9516
FR2HPP	0.1095	0.0815	0.0280
AS	0.0514	0.0548	-0.0034
FR	25.5781	21.6995	3.8785
FR2	-0.4301	-0.3161	-0.1141
BR	-1.9362	-2.1006	0.1643
LR	0.1135	0.1644	-0.0509
HPI	0.2487	0.2012	0.0474
MR	-308.4581	-292.0275	-16.4306
IC	126.4559	77.0973	49.3586
NS	2.4522	2.3182	0.1340
_cons	-563.5997	-809.2254	245.6256
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 199.97		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.53: Results of Sargan Test for GMM (HPP FRHPP and FR2HPP as endogenous variables, IFA GR IFAFR IFAFR2 GRFR and GRFR2 as instruments)

	Coef.	**Std. Err.**	**t**	**P-value**	**[95% Conf. Interval]**	
HPP	-4.9872	11.1831	-0.45	0.656	-26.9056	16.9311
FRHPP	-6.4909	0.6665	-9.74	0	-7.7972	-5.1846
FR2HPP	0.1112	0.0122	9.09	0	0.0872	0.1351
AS	0.0530	0.0042	12.54	0	0.0447	0.0613
FR	25.7721	2.6679	9.66	0	20.5431	31.0012
FR2	-0.4370	0.0491	-8.9	0	-0.5332	-0.3408
BR	-1.9445	0.2599	-7.48	0	-2.4539	-1.4352
LR	-0.0026	0.3053	-0.01	0.993	-0.6009	0.5958
HPI	0.2609	0.0239	10.93	0	0.2141	0.3077
MR	-308.7417	19.7601	-15.62	0	-347.4708	-270.0126
IC	127.8006	2.4629	51.89	0	122.9734	132.6277
NS	2.6020	0.4831	5.39	0	1.6550	3.5489
_cons	-552.8503	38.5438	-14.34	0	-628.3947	-477.3059
Sargan Test	chi2(1) = 2.8907					
	p = 0.4088					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.54: Results of Endogenous Test for GMM (HPP FRHPP and FR2HPP as endogenous variables, IFA GR IFAFR IFAFR2 GRFR and GRFR2 as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
HPP	0.8719	0.8718	0.2292	848.621	0
FRHPP	0.9998	0.9998	0.5635	3685.52	0
FR2HPP	0.9999	0.9999	0.672	5847.16	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
HPP	0.4091		0.4086		
FRHPP	0.726		0.7258		
FR2HPP	0.6912		0.691		
Wald test for weak instruments (Critical Values)					
	5%		10%	20%	30%
Maximal IV Size	12.2		7.77	5.35	4.4

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.55: Results of Hausman Test for GMM in Panel Model (HPP FRHPP and FR2HPP as endogenous variables, IFA GR IFAFR IFAFR2 GRFR and GRFR2 as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
HPP	3.9297	118.0117	-114.0820
FRHPP	-6.5570	-5.5937	-0.9633
FR2HPP	0.1034	0.0777	0.0258
AS	0.0587	0.0617	-0.0030
FR	26.3427	22.4138	3.9290
FR2	-0.4085	-0.3036	-0.1049
BR	-2.4893	-2.6302	0.1409
LR	0.3990	0.4467	-0.0477
HPI	0.2389	0.1931	0.0458
MR	-295.0656	-278.7437	-16.3219
IC	127.4720	79.3844	48.0876
NS	2.6293	2.4784	0.1508
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 212.21		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.56: Results of Sargan Test for GMM in Panel Model (HPP FRHPP and FR2HPP as endogenous variables, IFA GR IFAFR IFAFR2 GRFR and GRFR2 as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
HPP	3.9297	12.2730	0.32	0.749	-20.1248	27.9843
FRHPP	-6.5570	0.7103	-9.23	0	-7.9491	-5.1649
FR2HPP	0.1034	0.0160	6.46	0	0.0721	0.1348
AS	0.0587	0.0038	15.45	0	0.0513	0.0662
FR	26.3427	2.8899	9.12	0	20.6786	32.0069
FR2	-0.4085	0.0651	-6.28	0	-0.5361	-0.2809
BR	-2.4893	0.2664	-9.35	0	-3.0114	-1.9672
LR	0.3990	0.2855	1.4	0.162	-0.1606	0.9586
HPI	0.2389	0.0207	11.53	0	0.1983	0.2795
MR	-295.0656	29.3304	-10.06	0	-352.5520	-237.5791
IC	127.4720	4.0184	31.72	0	119.5961	135.3478
NS	2.6293	0.3609	7.29	0	1.9220	3.3366
Sargan Test	chi2(1) = 0.63					
	p = 0.8895					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.57: Results of Endogenous Test for GMM in Panel Model (HPP FRHPP and FR2HPP as endogenous variables, IFA GR IFAFR IFAFR2 GRFR and GRFR2 as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
HPP FRHPP FR2HPP	396.742		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	12.2	7.77	5.35	4.4

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.58: Results of Breusch-Pagan Test for Heteroskedasticity in OLS Estimator (without orientation)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
AS	0.06	0.00	14.46	0	0.0484	0.0636
FR	23.11	2.56	9.03	0	18.0918	28.1302
FR2	-0.34	0.06	-6.01	0	-0.4488	-0.2280
BR	0.06	0.40	0.15	0.878	-0.7303	0.8540
BRFR	-0.10	0.02	-6.2	0	-0.1355	-0.0704
LR	0.36	0.30	1.22	0.221	-0.2178	0.9435
HPP	121.60	8.15	14.91	0	105.6225	137.5870
FRHPP	-5.78	0.63	-9.2	0	-7.0122	-4.5488
FR2HPP	0.09	0.01	6.26	0	0.0595	0.1137
HPI	0.20	0.02	9.47	0	0.1598	0.2432
MR	-296.52	30.48	-9.73	0	-356.2499	-236.7813
IC	77.37	2.17	35.6	0	73.1095	81.6287
_cons	-828.41	29.12	-28.45	0	-885.4830	-771.3293
Breusch-Pagan test	chi2(1) = 9.22					
	Prob > chi2 = 0.0024					

Notes: This table provides results of the Breusch-Pagan test. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.59: Results of Breusch-Godfrey LM Test for Autocorrelation in OLS Estimator (without orientation)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
AS	0.06	0.00	14.46	0	0.0484	0.0636
FR	23.11	2.56	9.03	0	18.0918	28.1302
FR2	-0.34	0.06	-6.01	0	-0.4488	-0.2280
BR	0.06	0.40	0.15	0.878	-0.7303	0.8540
BRFR	-0.10	0.02	-6.2	0	-0.1355	-0.0704
LR	0.36	0.30	1.22	0.221	-0.2178	0.9435
HPP	121.60	8.15	14.91	0	105.6225	137.5870
FRHPP	-5.78	0.63	-9.2	0	-7.0122	-4.5488
FR2HPP	0.09	0.01	6.26	0	0.0595	0.1137
HPI	0.20	0.02	9.47	0	0.1598	0.2432
MR	-296.52	30.48	-9.73	0	-356.2499	-236.7813
IC	77.37	2.17	35.6	0	73.1095	81.6287
_cons	-828.41	29.12	-28.45	0	-885.4830	-771.3293
Breusch-Godfrey LM test	lags(p) = 1					
	chi2 = 130.612					
	df = 1					
	Prob > chi2 = 0					

Notes: This table provides results of the Breusch-Godfrey LM test. The null hypothesis of Breusch-Godfrey LM is that there is no serial correlation in the model.

Table A.60: Results of Hausman Test in Panel Model (without orientation)

	(b) Fixed	(B) Random	(b-B) Difference
AS	0.0628	0.0560	0.0068
FR	23.5122	23.1110	0.4012
FR2	-0.3212	-0.3384	0.0171
BR	-0.8894	0.0619	-0.9512
BRFR	-0.0778	-0.1030	0.0251
LR	0.6281	0.3629	0.2653
HPP	120.9582	121.6047	-0.6466
FRHPP	-5.8230	-5.7805	-0.0425
FR2HPP	0.0818	0.0866	-0.0048
HPI	0.1940	0.2015	-0.0074
MR	-283.5479	-296.5156	12.9677
IC	79.5524	77.3691	2.1833
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 669.69		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.61: Results of Wooldridge Test for Autocorrelation in Panel Model (without orientation)

	Coef.	Robust Std. Err.	t	P-value	[95% Conf. Interval]	
AS D1.	0.0667	0.0152	4.4	0.005	0.0296	0.1039
FR D1.	26.4089	12.5139	2.11	0.079	-4.2114	57.0293
FR2 D1.	-0.3805	0.1697	-2.24	0.066	-0.7958	0.0349
BR D1.	-1.1686	0.4332	-2.7	0.036	-2.2286	-0.1085
BRFR D1.	-0.0814	0.0207	-3.93	0.008	-0.1322	-0.0307
LR D1.	0.8445	0.5548	1.52	0.179	-0.5131	2.2021
HPP D1.	125.4494	38.3080	3.27	0.017	31.7131	219.1858
FRHPP D1.	-6.5445	3.1272	-2.09	0.081	-14.1966	1.1075
FR2HPP D1.	0.0964	0.0424	2.27	0.063	-0.0074	0.2002
HPI D1.	0.1724	0.0163	10.58	0	0.1325	0.2123
MR D1.	-283.6573	87.8508	-3.23	0.018	-498.6204	-68.6943
IC D1.	79.5517	7.8000	10.2	0	60.4658	98.6376
Wooldridge Test	F(1,6) = 0.793					
	Prob > F = 0.4074					

Notes: This table provides results of the Wooldridge test. The null hypothesis is that there is no first-order autocorrelation in the model.

Table A.62: Results of Likelihood-ratio Test for Groupwise Heteroskedasticity in Panel Model (without orientation)

Cross-sectional time-series FGLS regression						
Coefficients: generalized least squares						
Panels: heteroskedastic						
	Coef.	**Std. Err.**	**z**	**P-value**	**[95% Conf. Interval]**	
AS	0.0635	0.0030	21.01	0	0.0576	0.0694
FR	7.8226	2.1293	3.67	0	3.6493	11.9959
FR2	-0.1298	0.0431	-3.01	0.003	-0.2144	-0.0453
BR	-0.3963	0.3598	-1.1	0.271	-1.1015	0.3089
BRFR	-0.0966	0.0140	-6.91	0	-0.1241	-0.0692
LR	0.1362	0.2373	0.57	0.566	-0.3289	0.6012
HPP	64.2774	7.2724	8.84	0	50.0238	78.5310
FRHPP	-1.9534	0.5219	-3.74	0	-2.9763	-0.9304
FR2HPP	0.0345	0.0106	3.26	0.001	0.0138	0.0553
HPI	0.2051	0.0172	11.93	0	0.1714	0.2388
MR	-237.5752	25.1700	-9.44	0	-286.9074	-188.2430
IC	73.1115	1.7865	40.92	0	69.6099	76.6130
_cons	-584.7025	26.7845	-21.83	0	-637.1991	-532.2059
Panels: homoskedastic						
P	**Coef.**	**Std. Err.**	**z**	**P-value**	**[95% Conf. Interval]**	
AS	0.0560	0.0039	14.47	0	0.0484	0.0636
FR	23.1110	2.5597	9.03	0	18.0941	28.1279
FR2	-0.3384	0.0563	-6.01	0	-0.4487	-0.2280
BR	0.0619	0.4040	0.15	0.878	-0.7299	0.8537
BRFR	-0.1030	0.0166	-6.2	0	-0.1355	-0.0704
LR	0.3629	0.2961	1.23	0.22	-0.2176	0.9433
HPP	121.6047	8.1507	14.92	0	105.6297	137.5798
FRHPP	-5.7805	0.6281	-9.2	0	-7.0117	-4.5494
FR2HPP	0.0866	0.0138	6.26	0	0.0595	0.1137
HPI	0.2015	0.0213	9.47	0	0.1598	0.2432
MR	-296.5156	30.4635	-9.73	0	-356.2230	-236.8082
IC	77.3691	2.1723	35.62	0	73.1114	81.6268
_cons	-828.4061	29.1083	-28.46	0	-885.4573	-771.3549
Likelihood-ratio Test	LR chi2(6) = 4011.58					
	Prob > chi2 = 0.00					

Notes: This table provides results of the Likelihood-ratio test. The null hypothesis is that homoscedastic is nested in heteroskedastic.

Table A.63: Results of Friedman's Test for Cross-sectional Correlation in Panel Model (without orientation)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
AS	0.0628	0.0037	16.89	0	0.0555	0.0701
FR	23.5122	2.4274	9.69	0	18.7543	28.2701
FR2	-0.3212	0.0532	-6.03	0	-0.4256	-0.2169
BR	-0.8894	0.3867	-2.3	0.021	-1.6474	-0.1313
BRFR	-0.0778	0.0158	-4.93	0	-0.1088	-0.0469
LR	0.6281	0.2799	2.24	0.025	0.0795	1.1768
HPP	120.9582	7.7325	15.64	0	105.8017	136.1146
FRHPP	-5.8230	0.5954	-9.78	0	-6.9901	-4.6559
FR2HPP	0.0818	0.0131	6.25	0	0.0562	0.1074
HPI	0.1940	0.0201	9.66	0	0.1547	0.2334
MR	-283.5479	28.7567	-9.86	0	-339.9139	-227.1819
IC	79.5524	2.0530	38.75	0	75.5282	83.5766
_cons	-839.5595	27.6761	-30.34	0	-893.8075	-785.3115
Friedman's Test	Cross sectional independence = 266.36					
	Pr = 0.00					

Notes: This table provides results of the Friedman's test. The null hypothesis is there is no cross-sectional correlation in the model.

Table A.64: Results of Hausman Test for GMM (BR and BRFR as endogenous variables, SE NW FRSE and FRNW as instruments)

	(b)	(B)	(b-B)
	iv	ols	Difference
BR	-16.5471	0.0619	-16.6090
BRFR	0.1703	-0.1030	0.2733
AS	0.1710	0.0560	0.1150
FR	15.6338	23.1110	-7.4771
FR2	-0.2362	-0.3384	0.1022
LR	4.2550	0.3629	3.8921
HPP	107.9600	121.6047	-13.6448
FRHPP	-4.1710	-5.7805	1.6095
FR2HPP	0.0623	0.0866	-0.0243
HPI	0.2054	0.2015	0.0039
MR	-296.1182	-296.5156	0.3974
IC	73.9063	77.3691	-3.4628
_cons	-734.9127	-828.4061	93.4934
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 6.89		
	Prob>chi2 = 0.0319		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.65: Results of First Stage Regression for GMM (BR and BRFR as endogenous variables, SE NW FRSE and FRNW as instruments)

BR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	9.78E-03	1.20E-04	81.4	0	9.55E-03	1.00E-02
FR	-2.88E-01	6.90E-02	-4.18	0	-4.23E-01	-1.53E-01
FR2	3.75E-03	1.34E-03	2.79	0.005	1.11E-03	6.38E-03
LR	3.47E-01	9.36E-03	37.11	0	3.29E-01	3.66E-01
HPP	-4.13E-01	2.48E-01	-1.67	0.095	-8.99E-01	7.18E-02
FRHPP	6.96E-02	1.69E-02	4.11	0	3.64E-02	1.03E-01
FR2HPP	-9.91E-04	3.31E-04	-3	0.003	-1.64E-03	-3.42E-04
HPI	9.03E-05	5.95E-04	0.15	0.879	-1.08E-03	1.26E-03
MR	-2.22E-01	8.95E-01	-0.25	0.804	-1.98E+00	1.53E+00
IC	-2.38E-01	6.27E-02	-3.8	0	-3.61E-01	-1.15E-01
SE	-1.74E-01	5.25E-02	-3.31	0.001	-2.77E-01	-7.08E-02
NW	-2.52E-01	5.33E-02	-4.72	0	-3.56E-01	-1.47E-01
FRSE	1.27E-02	2.19E-03	5.77	0	8.35E-03	1.70E-02
FRNW	1.20E-02	2.30E-03	5.23	0	7.51E-03	1.65E-02
_cons	3.53E+00	8.89E-01	3.97	0	1.79E+00	5.27E+00

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

BRFR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	1.75E-01	3.08E-03	56.81	0	1.69E-01	1.81E-01
FR	1.06E+01	1.89E+00	5.6	0	6.88E+00	1.43E+01
FR2	-1.60E-01	4.21E-02	-3.81	0	-2.43E-01	-7.80E-02
LR	6.87E+00	2.11E-01	32.51	0	6.46E+00	7.29E+00
HPP	2.69E+01	5.92E+00	4.55	0	1.53E+01	3.85E+01
FRHPP	-1.82E+00	4.65E-01	-3.93	0	-2.74E+00	-9.14E-01
FR2HPP	3.20E-02	1.04E-02	3.09	0.002	1.17E-02	5.23E-02
HPI	-7.24E-03	1.45E-02	-0.5	0.617	-3.56E-02	2.11E-02
MR	-1.27E+01	2.11E+01	-0.6	0.549	-5.41E+01	2.87E+01
IC	-2.08E+00	1.49E+00	-1.4	0.162	-5.00E+00	8.35E-01
SE	-1.13E+01	1.13E+00	-10.06	0	-1.35E+01	-9.11E+00
NW	-7.64E-02	1.27E+00	-0.06	0.952	-2.57E+00	2.42E+00
FRSE	6.97E-01	5.02E-02	13.89	0	5.99E-01	7.96E-01
FRNW	1.09E-02	6.29E-02	0.17	0.862	-1.12E-01	1.34E-01
_cons	-1.36E+02	2.12E+01	-6.4	0	-1.78E+02	-9.42E+01

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.66: Results of Sargan Test for GMM (BR and BRFR as endogenous variables, SE NW FRSE and FRNW as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
BR	-21.1236	7.7885	-2.71	0.007	-36.3888	-5.8584
BRFR	0.2425	0.1704	1.42	0.155	-0.0915	0.5765
AS	0.2028	0.0485	4.18	0	0.1077	0.2978
FR	13.4942	4.8409	2.79	0.005	4.0063	22.9821
FR2	-0.2077	0.0748	-2.78	0.005	-0.3542	-0.0612
LR	5.3707	1.6615	3.23	0.001	2.1143	8.6272
HPP	102.8866	12.5345	8.21	0	78.3195	127.4537
FRHPP	-3.7043	1.0833	-3.42	0.001	-5.8275	-1.5811
FR2HPP	0.0555	0.0179	3.1	0.002	0.0204	0.0907
HPI	0.2015	0.0241	8.36	0	0.1543	0.2488
MR	-296.5277	22.0128	-13.47	0	-339.6719	-253.3834
IC	73.3106	2.2039	33.26	0	68.9910	77.6302
_cons	-705.0948	61.8320	-11.4	0	-826.2832	-583.9063
Sargan Test	chi2(1) = 5.86167					
	p = 0.0534					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.67: Results of Endogenous Test for GMM (BR and BRFR as endogenous variables, SE NW FRSE and FRNW as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
BR	0.6976	0.6974	0.0085	36.8455	0
BRFR	0.7643	0.7641	0.0279	122.778	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
BR	0.0034		0.0027		
BRFR	0.0111		0.0104		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	16.87		9.93	7.54	6.28

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.68: Results of First Stage Regression for GMM (BR and BRFR as endogenous variables, NW WE FRNW and FRWE as instruments)

BR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	9.82E-03	1.21E-04	81.19	0	9.58E-03	1.01E-02
FR	-2.56E-01	6.49E-02	-3.94	0	-3.83E-01	-1.29E-01
FR2	3.07E-03	1.17E-03	2.63	0.009	7.82E-04	5.37E-03
LR	3.50E-01	9.44E-03	37.12	0	3.32E-01	3.69E-01
HPP	-3.41E-01	2.45E-01	-1.39	0.163	-8.20E-01	1.38E-01
FRHPP	6.18E-02	1.59E-02	3.88	0	3.06E-02	9.31E-02
FR2HPP	-8.22E-04	2.87E-04	-2.86	0.004	-1.39E-03	-2.58E-04
HPI	-2.23E-05	5.96E-04	-0.04	0.97	-1.19E-03	1.15E-03
MR	-2.03E-01	8.94E-01	-0.23	0.821	-1.96E+00	1.55E+00
IC	-2.43E-01	6.29E-02	-3.87	0	-3.67E-01	-1.20E-01
NW	-2.39E-01	5.34E-02	-4.49	0	-3.44E-01	-1.35E-01
WE	-1.55E-01	6.41E-02	-2.42	0.016	-2.81E-01	-2.92E-02
FRNW	1.08E-02	2.30E-03	4.69	0	6.30E-03	1.53E-02
FRWE	1.43E-02	3.56E-03	4.03	0	7.35E-03	2.13E-02
_cons	3.26E+00	8.74E-01	3.72	0	1.54E+00	4.97E+00

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

BRFR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	1.76E-01	3.12E-03	56.55	0	1.70E-01	1.82E-01
FR	1.23E+01	2.12E+00	5.83	0	8.18E+00	1.65E+01
FR2	-1.96E-01	4.93E-02	-3.98	0	-2.93E-01	-9.97E-02
LR	7.03E+00	2.17E-01	32.45	0	6.61E+00	7.46E+00
HPP	3.10E+01	6.20E+00	5	0	1.88E+01	4.31E+01
FRHPP	-2.24E+00	5.20E-01	-4.31	0	-3.26E+00	-1.22E+00
FR2HPP	4.10E-02	1.21E-02	3.38	0.001	1.72E-02	6.48E-02
HPI	-1.28E-02	1.46E-02	-0.88	0.381	-4.15E-02	1.59E-02
MR	-1.31E+01	2.13E+01	-0.62	0.537	-5.49E+01	2.86E+01
IC	-2.33E+00	1.51E+00	-1.54	0.122	-5.29E+00	6.27E-01
NW	7.80E-01	1.29E+00	0.61	0.544	-1.74E+00	3.30E+00
WE	-1.30E+00	1.53E+00	-0.85	0.395	-4.29E+00	1.69E+00
FRNW	-5.61E-02	6.33E-02	-0.89	0.376	-1.80E-01	6.80E-02
FRWE	2.78E-01	1.01E-01	2.77	0.006	8.11E-02	4.75E-01
_cons	-1.52E+02	2.24E+01	-6.77	0	-1.96E+02	-1.08E+02

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.69: Results of Hausman Test for GMM (BR and BRFR as endogenous variables, NW WE FRNW and FRWE as instruments)

	(b) iv	(B) ols	(b-B) Difference
BR	-10.0193	0.0619	-10.0812
BRFR	0.6722	-0.1030	0.7752
AS	0.0184	0.0560	-0.0376
FR	11.0233	23.1110	-12.0877
FR2	-0.1562	-0.3384	0.1822
LR	-1.5827	0.3629	-1.9456
HPP	94.2587	121.6047	-27.3460
FRHPP	-3.4283	-5.7805	2.3522
FR2HPP	0.0468	0.0866	-0.0399
HPI	0.2126	0.2015	0.0111
MR	-288.3613	-296.5156	8.1544
IC	76.7135	77.3691	-0.6557
_cons	-678.6653	-828.4061	149.7408
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 7.29		
	Prob>chi2 = 0.0261		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.70: Results of Sargan Test for GMM (BR and BRFR as endogenous variables, NW WE FRNW and FRWE as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
BR	-8.3823	8.1794	-1.02	0.305	-24.4136	7.6491
BRFR	0.6291	0.2804	2.24	0.025	0.0795	1.1786
AS	0.0100	0.0527	0.19	0.85	-0.0934	0.1133
FR	11.9300	5.9413	2.01	0.045	0.2853	23.5747
FR2	-0.1680	0.0928	-1.81	0.07	-0.3499	0.0140
LR	-1.8528	1.8720	-0.99	0.322	-5.5218	1.8162
HPP	96.4537	14.7960	6.52	0	67.4541	125.4534
FRHPP	-3.6153	1.2721	-2.84	0.004	-6.1085	-1.1221
FR2HPP	0.0495	0.0216	2.29	0.022	0.0070	0.0919
HPI	0.2126	0.0237	8.97	0	0.1662	0.2591
MR	-288.5728	20.9098	-13.8	0	-329.5552	-247.5904
IC	76.9197	2.1110	36.44	0	72.7822	81.0571
_cons	-691.3921	75.0659	-9.21	0	-838.5186	-544.2657
Sargan Test	chi2(1) = 1.58489					
	p = 0.4527					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.71: Results of Endogenous Test for GMM (BR and BRFR as endogenous variables, NW WE FRNW and FRWE as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
BR	0.6958	0.6955	0.0025	10.7233	0
BRFR	0.758	0.7578	0.0022	9.4635	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
BR	0.0038		0.003		
BRFR	0.0033		0.0026		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	16.87		9.93	7.54	6.28

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.72: Results of Hausman Test for GMM in Panel Model (BR and BRFR as endogenous variables, SE SW FRSE and FRSW as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
BR	-31.5447	-0.8894	-30.6553
BRFR	0.5502	-0.0778	0.6281
AS	0.2575	0.0628	0.1947
FR	10.4078	23.5122	-13.1045
FR2	-0.1422	-0.3212	0.1790
LR	6.6865	0.6281	6.0583
HPP	96.3404	120.9582	-24.6178
FRHPP	-3.0770	-5.8230	2.7461
FR2HPP	0.0398	0.0818	-0.0420
HPI	0.2013	0.1940	0.0073
MR	-289.4630	-283.5479	-5.9151
IC	75.2699	79.5524	-4.2825
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 24.32		
	Prob>chi2 = 0.00		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.73: Results of First Stage Regression for GMM (BR and BRFR as endogenous variables, SE SW FRSE and FRSW as instruments)

BR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	0.0099	0.0001	125.02	0	0.0098	0.0101
FR	-0.2285	0.0712	-3.21	0.001	-0.3680	-0.0890
FR2	0.0030	0.0016	1.91	0.056	-0.0001	0.0061
LR	0.3338	0.0078	42.61	0	0.3184	0.3491
HPP	-0.2676	0.2272	-1.18	0.239	-0.7129	0.1777
FRHPP	0.0560	0.0175	3.2	0.001	0.0217	0.0903
FR2HPP	-0.0008	0.0004	-2.11	0.035	-0.0016	-0.0001
HPI	0.0001	0.0006	0.23	0.822	-0.0010	0.0013
MIR	-0.6785	0.8466	-0.8	0.423	-2.3379	0.9808
IC	-0.1691	0.0604	-2.8	0.005	-0.2875	-0.0507
SE	-0.1459	0.0414	-3.53	0	-0.2271	-0.0648
SW	-0.0185	0.0547	-0.34	0.735	-0.1257	0.0887
FRSE	0.0125	0.0017	7.31	0	0.0091	0.0158
FRSW	0.0100	0.0023	4.39	0	0.0055	0.0145

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

BRFR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	0.1750	0.0019	91.76	0	0.1713	0.1787
FR	9.6048	1.7124	5.61	0	6.2483	12.9614
FR2	-0.1377	0.0377	-3.66	0	-0.2115	-0.0639
LR	6.6365	0.1885	35.21	0	6.2670	7.0059
HPP	25.0583	5.4670	4.58	0	14.3424	35.7741
FRHPP	-1.6032	0.4208	-3.81	0	-2.4280	-0.7783
FR2HPP	0.0266	0.0093	2.88	0.004	0.0085	0.0448
HPI	-0.0047	0.0142	-0.33	0.742	-0.0326	0.0232
MIR	-16.6162	20.3714	-0.82	0.415	-56.5462	23.3139
IC	-1.5318	1.4534	-1.05	0.292	-4.3807	1.3170
SE	-11.5760	0.9961	-11.62	0	-13.5285	-9.6234
SW	-7.4813	1.3158	-5.69	0	-10.0604	-4.9022
FRSE	0.7429	0.0411	18.06	0	0.6623	0.8235
FRSW	0.6176	0.0548	11.27	0	0.5102	0.7250

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.74: Results of Sargan Test for GMM in Panel Model (BR and BRFR as endogenous variables, SE SW FRSE and FRSW as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
BR	-31.5447	8.1585	-3.87	0	-47.5350	-15.5544
BRFR	0.5502	0.1992	2.76	0.006	0.1597	0.9407
AS	0.2575	0.0485	5.31	0	0.1624	0.3526
FR	10.4078	4.8015	2.17	0.03	0.9970	19.8186
FR2	-0.1422	0.0829	-1.72	0.086	-0.3047	0.0202
LR	6.6865	1.5229	4.39	0	3.7016	9.6713
HPP	96.3404	11.8343	8.14	0	73.1457	119.5351
FRHPP	-3.0770	1.0631	-2.89	0.004	-5.1605	-0.9934
FR2HPP	0.0398	0.0199	2	0.045	0.0009	0.0788
HPI	0.2013	0.0240	8.39	0	0.1543	0.2484
MR	-289.4630	34.2446	-8.45	0	-356.5811	-222.3448
IC	75.2699	2.6780	28.11	0	70.0212	80.5186
Sargan Test	chi2(1) = 5.848					
	p = 0.0537					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.75: Results of Endogenous Test for GMM in Panel Model (BR and BRFR as endogenous variables, SE SW FRSE and FRSW as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
BR BRFR	50.939		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	16.87	9.93	7.54	6.28

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A. 76: Results of First Stage Regression for GMM (BR and BRFR as endogenous variables, SE NW FRSE and FRNW as instruments)

BR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	0.0100	0.0001	125.21	0	0.0098	0.0101
FR	-0.2153	0.0715	-3.01	0.003	-0.3555	-0.0751
FR2	0.0025	0.0016	1.61	0.107	-0.0005	0.0056
LR	0.3383	0.0079	42.99	0	0.3229	0.3538
HPP	-0.2878	0.2284	-1.26	0.208	-0.7355	0.1599
FRHPP	0.0532	0.0176	3.03	0.002	0.0188	0.0877
FR2HPP	-0.0007	0.0004	-1.83	0.068	-0.0015	0.0001
HPI	0.0001	0.0006	0.23	0.822	-0.0010	0.0013
MIR	-0.4939	0.8508	-0.58	0.562	-2.1617	1.1738
IC	-0.1691	0.0607	-2.78	0.005	-0.2881	-0.0501
SE	-0.1565	0.0416	-3.76	0	-0.2380	-0.0750
NW	-0.2807	0.0579	-4.85	0	-0.3941	-0.1673
FRSE	0.0118	0.0017	6.87	0	0.0084	0.0152
FRNW	0.0123	0.0025	4.98	0	0.0074	0.0171

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

BRFR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	0.1770	0.0019	91.67	0	0.1732	0.1808
FR	10.4939	1.7350	6.05	0	7.0932	13.8946
FR2	-0.1630	0.0381	-4.27	0	-0.2378	-0.0882
LR	6.8148	0.1909	35.7	0	6.4406	7.1889
HPP	25.7510	5.5397	4.65	0	14.8926	36.6094
FRHPP	-1.7980	0.4264	-4.22	0	-2.6337	-0.9623
FR2HPP	0.0326	0.0094	3.48	0.001	0.0142	0.0510
HPI	-0.0023	0.0144	-0.16	0.872	-0.0306	0.0259
MIR	-12.3950	20.6374	-0.6	0.548	-52.8464	28.0565
IC	-1.5913	1.4730	-1.08	0.28	-4.4784	1.2959
SE	-11.4207	1.0085	-11.32	0	-13.3974	-9.4440
NW	-0.7090	1.4035	-0.51	0.613	-3.4600	2.0420
FRSE	0.6954	0.0416	16.71	0	0.6138	0.7769
FRNW	0.0216	0.0597	0.36	0.717	-0.0954	0.1386

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.77: Results of Hausman Test for GMM in Panel Model (BR and BRFR as endogenous variables, SE NW FRSE and FRNW as instruments)

	(b)	(B)	(b-B)
	iv	fe	Difference
BR	-18.9487	-0.8894	-18.0593
BRFR	0.1969	-0.0778	0.2747
AS	0.1946	0.0628	0.1317
FR	16.9626	23.5122	-6.5497
FR2	-0.2348	-0.3212	0.0864
LR	4.8641	0.6281	4.2360
HPP	109.3214	120.9582	-11.6368
FRHPP	-4.4175	-5.8230	1.4055
FR2HPP	0.0610	0.0818	-0.0207
HPI	0.1975	0.1940	0.0034
MR	-288.2494	-283.5479	-4.7015
IC	76.8547	79.5524	-2.6977
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 10.02		
	Prob>chi2 = 0.0067		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.78: Results of Sargan Test for GMM in Panel Model (BR and BRFR as endogenous variables, SE NW FRSE and FRNW as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
BR	-18.9487	6.9021	-2.75	0.006	-32.4765	-5.4209
BRFR	0.1969	0.1550	1.27	0.204	-0.1070	0.5007
AS	0.1946	0.0460	4.23	0	0.1044	0.2847
FR	16.9626	4.0057	4.23	0	9.1116	24.8135
FR2	-0.2348	0.0712	-3.3	0.001	-0.3743	-0.0953
LR	4.8641	1.4895	3.27	0.001	1.9447	7.7836
HPP	109.3214	10.1793	10.74	0	89.3702	129.2725
FRHPP	-4.4175	0.9000	-4.91	0	-6.1814	-2.6537
FR2HPP	0.0610	0.0172	3.56	0	0.0274	0.0947
HPI	0.1975	0.0218	9.07	0	0.1548	0.2401
MR	-288.2494	31.1042	-9.27	0	-349.2124	-227.2863
IC	76.8547	2.4226	31.72	0	72.1065	81.6029
Sargan Test	chi2(1) = 5.293					
	p = 0.0709					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.79: Results of Endogenous Test for GMM in Panel Model (BR and BRFR as endogenous variables, SE NW FRSE and FRNW as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
BR BRFR	53.94		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	16.87	9.93	7.54	6.28

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.80: Results of Hausman Test for GMM in Panel Model (BR and BRFR as endogenous variables, SW NW FRSW and FRNW as instruments)

	(b)	**(B)**	**(b-B)**
	iv	**fe**	**Difference**
BR	-20.6761	-0.8894	-19.7867
BRFR	0.3976	-0.0778	0.4754
AS	0.1760	0.0628	0.1132
FR	14.1939	23.5122	-9.3183
FR2	-0.1917	-0.3212	0.1295
LR	4.0484	0.6281	3.4203
HPP	102.9625	120.9582	-17.9956
FRHPP	-3.8946	-5.8230	1.9285
FR2HPP	0.0518	0.0818	-0.0300
HPI	0.1994	0.1940	0.0053
MR	-286.4716	-283.5479	-2.9237
IC	76.9167	79.5524	-2.6357
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 13.17		
	Prob>chi2 = 0.0014		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means fixed effect is appropriate.

Table A.81: Results of First Stage Regression for GMM (BR and BRFR as endogenous variables, SW NW FRSW and FRNW as instruments)

BR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	0.0100	0.0001	125.54	0	0.0098	0.0101
FR	-0.1954	0.0714	-2.74	0.006	-0.3353	-0.0556
FR2	0.0023	0.0016	1.46	0.144	-0.0008	0.0054
LR	0.3386	0.0079	43.09	0	0.3232	0.3540
HPP	-0.1962	0.2280	-0.86	0.39	-0.6431	0.2507
FRHPP	0.0481	0.0175	2.74	0.006	0.0137	0.0825
FR2HPP	-0.0006	0.0004	-1.65	0.098	-0.0014	0.0001
HPI	-0.0001	0.0006	-0.12	0.903	-0.0012	0.0011
MIR	-0.6163	0.8498	-0.73	0.468	-2.2820	1.0494
IC	-0.1782	0.0606	-2.94	0.003	-0.2971	-0.0594
SW	-0.0097	0.0548	-0.18	0.859	-0.1172	0.0978
NW	-0.2745	0.0578	-4.75	0	-0.3877	-0.1612
FRSW	0.0086	0.0023	3.77	0	0.0041	0.0131
FRNW	0.0121	0.0025	4.91	0	0.0073	0.0169

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

BRFR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	0.1772	0.0019	91.5	0	0.1734	0.1810
FR	11.6623	1.7409	6.7	0	8.2500	15.0747
FR2	-0.1809	0.0383	-4.72	0	-0.2560	-0.1059
LR	6.8703	0.1917	35.84	0	6.4946	7.2461
HPP	29.7789	5.5617	5.35	0	18.8775	40.6804
FRHPP	-2.0932	0.4278	-4.89	0	-2.9318	-1.2547
FR2HPP	0.0374	0.0094	3.97	0	0.0189	0.0558
HPI	-0.0119	0.0145	-0.82	0.412	-0.0402	0.0165
MIR	-15.8575	20.7297	-0.76	0.444	-56.4898	24.7747
IC	-1.8506	1.4791	-1.25	0.211	-4.7498	1.0485
SW	-6.3762	1.3377	-4.77	0	-8.9981	-3.7542
NW	-0.3513	1.4094	-0.25	0.803	-3.1139	2.4113
FRSW	0.5242	0.0557	9.41	0	0.4150	0.6333
FRNW	0.0009	0.0599	0.01	0.988	-0.1166	0.1184

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.82: Results of Sargan Test for GMM in Panel Model (BR and BRFR as endogenous variables, SW NW FRSW and FRNW as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
BR	-20.6761	6.1457	-3.36	0.001	-32.7213	-8.6308
BRFR	0.3976	0.1910	2.08	0.037	0.0233	0.7719
AS	0.1760	0.0342	5.14	0	0.1089	0.2431
FR	14.1939	4.2436	3.34	0.001	5.8765	22.5113
FR2	-0.1917	0.0747	-2.57	0.01	-0.3381	-0.0453
LR	4.0484	1.0985	3.69	0	1.8953	6.2015
HPP	102.9625	10.7366	9.59	0	81.9193	124.0058
FRHPP	-3.8946	0.9326	-4.18	0	-5.7225	-2.0666
FR2HPP	0.0518	0.0178	2.91	0.004	0.0169	0.0867
HPI	0.1994	0.0217	9.17	0	0.1568	0.2420
MR	-286.4716	31.0043	-9.24	0	-347.2389	-225.7043
IC	76.9167	2.3474	32.77	0	72.3158	81.5176
Sargan Test	chi2(1) = 4.81					
	p = 0.0903					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.83: Results of Endogenous Test for GMM in Panel Model (BR and BRFR as endogenous variables, SW NW FRSW and FRNW as instruments)

Underidentification test (Anderson canon. corr. LM statistic)				
Variable	Chi-sq(2)		Prob > F	
BR BRFR	77.926		0	
Wald test for weak instruments (Critical Values)				
	10%	15%	20%	25%
Maximal IV Size	16.87	9.93	7.54	6.28

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.84: Results of First Stage Regression for GMM (LR and LRFR as endogenous variables, W WE FRW and FRWE as instruments)

LR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	0.0026	0.0001	21.83	0	0.0024	0.0029
FR	0.1476	0.0630	2.34	0.019	0.0242	0.2710
FR2	-0.0017	0.0014	-1.25	0.212	-0.0044	0.0010
BR	0.2885	0.0072	40	0	0.2744	0.3026
HPP	0.3778	0.2069	1.83	0.068	-0.0278	0.7834
FRHPP	-0.0343	0.0155	-2.21	0.027	-0.0646	-0.0039
FR2HPP	0.0004	0.0003	1.14	0.256	-0.0003	0.0010
HPI	-0.0010	0.0005	-1.75	0.079	-0.0020	0.0001
MR	-0.2177	0.7820	-0.28	0.781	-1.7504	1.3151
IC	0.0772	0.0551	1.4	0.161	-0.0307	0.1851
W	-0.2247	0.0358	-6.28	0	-0.2948	-0.1545
WE	0.0481	0.0552	0.87	0.384	-0.0602	0.1563
FRW	0.0092	0.0014	6.66	0	0.0065	0.0119
FRWE	0.0013	0.0031	0.42	0.674	-0.0047	0.0073
_cons	-1.3642	0.7351	-1.86	0.064	-2.8051	0.0768

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

LRFR	Coef.	Robust Std. Err.	t	P>t	[95% Conf.Interval]	
AS	0.0444	0.0025	17.66	0	0.0395	0.0493
FR	11.0007	2.5672	4.29	0	5.9687	16.0326
FR2	-0.1371	0.0691	-1.98	0.047	-0.2726	-0.0016
BR	5.6959	0.1506	37.82	0	5.4007	5.9911
HPP	24.8288	5.5792	4.45	0	13.8930	35.7646
FRHPP	-2.2459	0.6319	-3.55	0	-3.4845	-1.0074
FR2HPP	0.0319	0.0170	1.88	0.061	-0.0014	0.0652
HPI	-0.0144	0.0127	-1.13	0.258	-0.0394	0.0106
MR	-5.9899	17.5482	-0.34	0.733	-40.3861	28.4063
IC	1.6577	1.2485	1.33	0.184	-0.7894	4.1049
W	2.9770	1.0673	2.79	0.005	0.8849	5.0690
WE	0.8340	0.9182	0.91	0.364	-0.9657	2.6337
FRW	-0.1434	0.0525	-2.73	0.006	-0.2462	-0.0406
FRWE	0.0717	0.0624	1.15	0.251	-0.0507	0.1940
_cons	-129.4946	20.4968	-6.32	0	-169.6705	-89.3188

Notes: This table provides results of the first stage regression of IV-GMM. The null hypothesis is that instrumental variables have not relationship to the endogenous variable (instrumental variables are exogenous).

Table A.85: Results of Hausman Test for GMM (LR and LRFR as endogenous variables, W WE FRW and FRWE as instruments)

	(b)	(B)	(b-B)
	iv	ols	Difference
LR	6.8788	3.1651	3.7137
LRFR	0.6339	-0.1457	0.7796
AS	0.0109	0.0551	-0.0442
FR	13.3220	22.6862	-9.3641
FR2	-0.2113	-0.3315	0.1201
BR	-7.3422	-1.8075	-5.5347
HPP	99.4043	120.5410	-21.1367
FRHPP	-3.7615	-5.6960	1.9345
FR2HPP	0.0575	0.0853	-0.0279
HPI	0.2193	0.2031	0.0162
MR	-290.6159	-295.7416	5.1256
IC	75.5826	77.2016	-1.6189
_cons	-715.0976	-822.7266	107.6290
Hausman Test	chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)		
	= 6.45		
	Prob>chi2 = 0.0397		

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means ols estimator is appropriate.

Table A.86: Results of Sargan Test for GMM (LR and LRFR as endogenous variables, W WE FRW and FRWE as instruments)

	Coef.	Std. Err.	t	P-value	[95% Conf. Interval]	
LR	5.9380	4.9725	1.19	0.232	-3.8079	15.6839
LRFR	0.6167	0.2619	2.35	0.019	0.1033	1.1301
AS	0.0141	0.0194	0.73	0.467	-0.0239	0.0521
FR	13.9546	4.6339	3.01	0.003	4.8723	23.0369
FR2	-0.2194	0.0804	-2.73	0.006	-0.3771	-0.0617
BR	-6.9760	2.2690	-3.07	0.002	-11.4231	-2.5288
HPP	101.5377	13.0201	7.8	0	76.0188	127.0565
FRHPP	-3.9092	1.0608	-3.69	0	-5.9883	-1.8301
FR2HPP	0.0594	0.0196	3.04	0.002	0.0211	0.0977
HPI	0.2160	0.0266	8.12	0	0.1638	0.2682
MR	-291.7102	23.4907	-12.42	0	-337.7510	-245.6693
IC	75.7580	1.9580	38.69	0	71.9204	79.5956
_cons	-724.0563	55.5669	-13.03	0	-832.9655	-615.1472
Sargan Test	chi2(1) = 2.0211					
	p = 0.364					

Notes: This table provides results of the Sargan test. The null hypothesis is that instrumental variables have not relationship to the error (instrumental variables are exogenous).

Table A.87: Results of Endogenous Test for GMM (LR and LRFR as endogenous variables, W WE FRW and FRWE as instruments)

First-stage regression summary statistics					
Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(2,17129)	Prob > F
LR	0.4345	0.434	0.003	12.7745	0
LRFR	0.6523	0.652	0.0019	8.07706	0
Shea's partial R-squared					
Variable	Shea's Partial R-sq.		Shea's Adj. Partial R-sq.		
LR	0.0095		0.0088		
LRFR	0.006		0.0053		
Wald test for weak instruments (Critical Values)					
	10%		15%	20%	25%
Maximal IV Size	16.87		9.93	7.54	6.28

Notes: This table provides results of the endogenous test. The null hypothesis is that instrumental variables are not relative to endogenous variables. For Wald test, the null hypothesis is that the instruments are weak.

Table A.88 – Table A.143 are belonging to **Chapter 5 The Spatial Analysis and Spill-over Effects of House Price in Beijing**

Table A.88: Variable List

Name	Variables	Code
P	House Price	price
NP	Number of projects newly started (excluding rural households) (unit)	s2
BS	Floor space of buildings started this year of enterprises for real estate development, residential (10000 sq.m)	s8
AW	Average wage of staff and workers (yuan)	s9
GDP	Gross domestic product (100 million yuan)	d1
Tax	Taxes and other charges on principal business of enterprises for real estate development (100 million yuan)	d2
UP	Urban population (% of total)	d4
UR	Unemployment, total (% of total labor force) (national estimate)	d7
IR	Central Bank Interest Rates (%)	d8
Dist_air	Distance between the region and Beijing Capital Airport	Dist1
Dist_CBD	Distance between the region and Beijing CBD	Dist3
Region	Chengnei district	1
Region	Chaoyang district	2
Region	Fengtai district	3
Region	Shijingshan district	4
Region	Haidian district	5
Region	Mentougou district	6
Region	Fangshan district	7
Region	Tongzhou district	8
Region	Shunyi district	9
Region	Changping district	10
Region	Daxing district	11
Region	Pinggu district	12
Region	Huairou district	13
Region	Miyun district	14
Region	Yanqing district	15

Notes: All variables were downloaded from the Beijing municipal commission on house and urban-rural development website. Data is from 2003 to 2013.

Table A.89: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
House Price	165	3.95	0.38	3.04	4.78
Number of New Projects	165	3.07	0.21	2.77	3.56
Size of Building Started	165	3.28	0.08	3.14	3.41
Average Wage	165	4.71	0.18	4.40	4.97
Income	165	4.02	0.19	3.70	4.30
Tax	165	2.23	0.28	1.72	2.60
Urban Population	165	1.67	0.04	1.60	1.73
Unemployment Rate	165	0.042	0.001	0.04	0.043
Central Bank Interest Rate	165	0.064	0.005	0.058	0.073
Distance to Beijing Capital Airport (km)	165	35,759	15,025	6,912	67,652
Distance to CBD (km)	165	33,303	19,788	6,303	74,130

Notes: This table summarises descriptive statistics (number of observations, sample mean, standard deviation, minimum and maximum) of the full sample of variables.

Table A.90: Models

Model 1.1	*Panel:* $logP_{it} = \alpha_0 + a_1 logNP_{it} + a_2 logBS_{it} + a_3 logAW_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} P_{it} + a_1 logNP_{it} + a_2 logBS_{it} + a_3 logAW_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$
Model 1.2	*Panel:* $logP_{it} = \alpha_0 + \tau logP_{it-1} + a_1 logNP_{it} + a_2 logBS_{it} + a_3 logAW_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \tau logP_{it-1} + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logNP_{it} + a_2 logBS_{it} + a_3 logAW_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$
Model 2.1	*Panel:* $logP_{it} = \alpha_0 + a_1 logGDP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logGDP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$

Model 2.2	*Panel:* $logP_{it} = \alpha_0 + \tau logP_{it-1} + a_1 logGDP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \tau logP_{it-1} + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logGDP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$
Model 3.1	*Panel:* $logP_{it} = \alpha_0 + a_1 logTAX_{it} + a_2 IR_{it} + a_3 Dist_{air} + +a_4 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logTAX_{it} + a_2 IR_{it} + a_3 Dist_{air} + +a_4 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$
Model 3.2	*Panel:* $logP_{it} = \alpha_0 + \tau logP_{it-1} + a_1 logTAX_{it} + a_2 IR_{it} + a_3 Dist_{air} + +a_4 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \tau logP_{it-1} + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logTAX_{it} + a_2 IR_{it} + a_3 Dist_{air} + +a_4 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{i=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$
Model 4.1	*Panel:* $logP_{it} = \alpha_0 + a_1 logUP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logUP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$
Model 4.2	*Panel:* $logP_{it} = \alpha_0 + \tau logP_{it-1} + a_1 logUP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + d_1 Region + d_2 Year$ *Spatial:* $logP_{it} = \alpha + \tau logP_{it-1} + \rho \sum_{j=1}^{N} W_{ij} logP_{it} + a_1 logUP_{it} + a_2 UR_{it} + a_3 IR_{it} + a_4 Dist_{air} + +a_5 Dist_{CBD} + \varepsilon_{it}$ $\varepsilon_{it} = \lambda \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + \nu_{it}$

Notes: This table summarises the models in the investigation.

Table A.91: Diagnostic Tests for Spatial Dependence in OLS Regression (Model 1.1)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	1.415	1	0.157
Lagrange multiplier	10.607	1	0.001
Robust Lagrange multiplier	8.062	1	0.005
Spatial lag:			
Lagrange multiplier	15.885	1	0
Robust Lagrange multiplier	13.34	1	0

Notes: This table provides the diagnostic tests for spatial dependence in OLS regression. The null hypothesis of spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of spatial lag test is that there is no spatially lagged dependent variable in the model.

Table A.92: Diagnostic Tests for Spatial Dependence in OLS Regression (Model 1.2)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	2.35	1	0.019
Lagrange multiplier	48.828	1	0
Robust Lagrange multiplier	48.162	1	0
Spatial lag:			
Lagrange multiplier	1.07	1	0.301
Robust Lagrange multiplier	0.404	1	0.525

Notes: This table provides the diagnostic tests for spatial dependence in OLS regression. The null hypothesis of spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of spatial lag test is that there is no spatially lagged dependent variable in the model.

Table A.93: Diagnostic Tests for Spatial Dependence in OLS Regression (Model 2.1)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	1.128	1	0.259
Lagrange multiplier	4.415	1	0.036
Robust Lagrange multiplier	2.859	1	0.091
Spatial lag:			
Lagrange multiplier	15.857	1	0
Robust Lagrange multiplier	14.302	1	0

Notes: This table provides the diagnostic tests for spatial dependence in OLS regression. The null hypothesis of spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of spatial lag test is that there is no spatially lagged dependent variable in the model.

Table A.94: Diagnostic Tests for Spatial Dependence in OLS Regression (Model 2.2)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	2.228	1	0.026
Lagrange multiplier	41.746	1	0
Robust Lagrange multiplier	40.964	1	0
Spatial lag:			
Lagrange multiplier	1.592	1	0.207
Robust Lagrange multiplier	0.81	1	0.368

Notes: This table provides the diagnostic tests for spatial dependence in OLS regression. The null hypothesis of spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of spatial lag test is that there is no spatially lagged dependent variable in the model.

Table A.95: Diagnostic Tests for Spatial Dependence in OLS Regression (Model 3.1)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	1.085	1	0.278
Lagrange multiplier	6.28	1	0.012
Robust Lagrange multiplier	4.381	1	0.036
Spatial lag:			
Lagrange multiplier	15.846	1	0
Robust Lagrange multiplier	13.947	1	0

Notes: This table provides the diagnostic tests for spatial dependence in OLS regression. The null hypothesis of spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of spatial lag test is that there is no spatially lagged dependent variable in the model.

Table A.96: Diagnostic Tests for Spatial Dependence in OLS Regression (Model 3.2)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	1.867	1	0.062
Lagrange multiplier	30.986	1	0
Robust Lagrange multiplier	30.269	1	0
Spatial lag:			
Lagrange multiplier	1.763	1	0.184
Robust Lagrange multiplier	1.046	1	0.306

Notes: This table provides the diagnostic tests for spatial dependence in OLS regression. The null hypothesis of spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of spatial lag test is that there is no spatially lagged dependent variable in the model.

Table A.97: Diagnostic Tests for Spatial Dependence in OLS Regression (Model 4.1)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	1.159	1	0.246
Lagrange multiplier	4.959	1	0.026
Robust Lagrange multiplier	3.297	1	0.069
Spatial lag:			
Lagrange multiplier	15.85	1	0
Robust Lagrange multiplier	14.188	1	0

Notes: This table provides the diagnostic tests for spatial dependence in OLS regression. The null hypothesis of spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of spatial lag test is that there is no spatially lagged dependent variable in the model.

Table A.98: Diagnostic Tests for Spatial Dependence in OLS Regression (Model 4.2)

Test	Statistic	df	p-value
Spatial error:			
Moran's I	2.247	1	0.025
Lagrange multiplier	42.682	1	0
Robust Lagrange multiplier	41.9	1	0
Spatial lag:			
Lagrange multiplier	1.561	1	0.211
Robust Lagrange multiplier	0.78	1	0.377

Notes: This table provides the diagnostic tests for spatial dependence in OLS regression. The null hypothesis of spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of spatial lag test is that there is no spatially lagged dependent variable in the model.

Table A.99: Moran's I of Global Spatial Autocorrelation (Model 1.1)

Variables	I	sd(I)	z	p-value*
price	0.736	0.052	14.156	0
s2	1	0.052	19.24	0
s8	1	0.053	19.15	0
s9	1	0.053	19.139	0
Dist1	0.189	0.052	3.715	0
Dist3	0.432	0.052	8.352	0

Notes: This table provides the Moran's I of global spatial autocorrelation. I is the value of Moran's I, sd(I) is standard error of Moran's I, z is z-stats.

Table A.100: Moran's I of Global Spatial Autocorrelation (Model 1.2)

Variables	I	sd(I)	z	p-value*
price	0.736	0.052	14.156	0
lag1_price	0.736	0.052	14.164	0
s2	1	0.052	19.24	0
s8	1	0.053	19.15	0
s9	1	0.053	19.139	0
Dist1	0.189	0.052	3.715	0
Dist3	0.432	0.052	8.352	0

Notes: This table provides the Moran's I of global spatial autocorrelation. I is the value of Moran's I, sd(I) is standard error of Moran's I, z is z-stats.

Table A.101: Moran's I of Global Spatial Autocorrelation (Model 2.1)

Variables	I	sd(I)	z	p-value*
price	0.736	0.052	14.156	0
d1	1	0.053	19.139	0
d7	1	0.053	19.151	0
d8	1	0.053	19.147	0
Dist1	0.189	0.052	3.715	0
Dist3	0.432	0.052	8.352	0

Notes: This table provides the Moran's I of global spatial autocorrelation. I is the value of Moran's I, sd(I) is standard error of Moran's I, z is z-stats.

Table A.102: Moran's I of Global Spatial Autocorrelation (Model 2.2)

Variables	I	sd(I)	z	p-value*
price	0.736	0.052	14.156	0
lag1_price	0.736	0.052	14.164	0
d1	1	0.053	19.139	0
d7	1	0.053	19.151	0
d8	1	0.053	19.147	0
Dist1	0.189	0.052	3.715	0
Dist3	0.432	0.052	8.352	0

Notes: This table provides the Moran's I of global spatial autocorrelation. I is the value of Moran's I, sd(I) is standard error of Moran's I, z is z-stats.

Table A.103: Moran's I of Global Spatial Autocorrelation (Model 3.1)

Variables	I	sd(I)	z	p-value*
price	0.736	0.052	14.156	0
d2	1	0.053	19.142	0
d8	1	0.053	19.147	0
Dist1	0.189	0.052	3.715	0
Dist3	0.432	0.052	8.352	0

Notes: This table provides the Moran's I of global spatial autocorrelation. I is the value of Moran's I, sd(I) is standard error of Moran's I, z is z-stats.

Table A.104: Moran's I of Global Spatial Autocorrelation (Model 3.2)

Variables	I	sd(I)	z	p-value*
price	0.736	0.052	14.156	0
lag1_price	0.736	0.052	14.164	0
d2	1	0.053	19.142	0
d8	1	0.053	19.147	0
Dist1	0.189	0.052	3.715	0
Dist3	0.432	0.052	8.352	0

Notes: This table provides the Moran's I of global spatial autocorrelation. I is the value of Moran's I, sd(I) is standard error of Moran's I, z is z-stats.

Table A.105: Moran's I of Global Spatial Autocorrelation (Model 4.1)

Variables	I	sd(I)	z	p-value*
price	0.736	0.052	14.156	0
d4	1	0.053	19.138	0
d7	1	0.053	19.151	0
d8	1	0.053	19.147	0
Dist1	0.189	0.052	3.715	0
Dist3	0.432	0.052	8.352	0

Notes: This table provides the Moran's I of global spatial autocorrelation. I is the value of Moran's I, sd(I) is standard error of Moran's I, z is z-stats.

Table A.106: Moran's I of Global Spatial Autocorrelation (Model 4.2)

Variables	I	sd(I)	z	p-value*
price	0.736	0.052	14.156	0
lag1_price	0.736	0.052	14.164	0
d4	1	0.053	19.138	0
d7	1	0.053	19.151	0
d8	1	0.053	19.147	0
Dist1	0.189	0.052	3.715	0
Dist3	0.432	0.052	8.352	0

Notes: This table provides the Moran's I of global spatial autocorrelation. I is the value of Moran's I, sd(I) is standard error of Moran's I, z is z-stats.

Table A.107: Measures of Local Spatial Autocorrelation for the House Prices

Location	Ii	sd(Ii)	z	p-value*
1	1.359	1.713	0.804	0.211
2	0.722	1.713	0.432	0.333
3	-0.036	1.713	-0.01	0.496
4	-0.258	1.713	-0.14	0.444
5	1.44	1.713	0.852	0.197
6	0.472	1.713	0.286	0.387
7	7.354	1.713	4.304	0
8	9.211	1.713	5.388	0
9	10.666	1.713	6.238	0
10	11.656	1.713	6.816	0
11	12.273	1.713	7.176	0
12	6.174	2.584	2.406	0.008
13	4.46	2.584	1.742	0.041
14	2.211	2.584	0.872	0.192
15	0.562	2.584	0.234	0.408
16	0.037	2.584	0.031	0.488
17	0.008	2.584	0.02	0.492
18	6.483	2.584	2.525	0.006
19	8.971	2.584	3.488	0
20	12.887	2.584	5.004	0
21	15.457	2.584	5.998	0
22	20.24	2.584	7.849	0
23	6	2.584	2.338	0.01
24	4.319	2.584	1.688	0.046
25	2.971	2.584	1.166	0.122
26	0.404	2.584	0.173	0.431
27	-0.02	2.584	0.009	0.496
28	-0.011	2.584	0.012	0.495
29	6.82	2.584	2.656	0.004
30	10.632	2.584	4.131	0
31	13.605	2.584	5.281	0
32	15.165	2.584	5.885	0
33	16.879	2.584	6.548	0
34	5.695	1.713	3.335	0
35	4.535	1.713	2.658	0.004

36	3.705	1.713	2.174	0.015
37	1.057	1.713	0.628	0.265
38	-0.839	1.713	-0.479	0.316
39	-0.497	1.713	-0.279	0.39
40	1.05	1.713	0.624	0.266
41	2.446	1.713	1.439	0.075
42	3.863	1.713	2.266	0.012
43	4.695	1.713	2.752	0.003
44	6.763	1.713	3.959	0
45	5.227	2.4	2.193	0.014
46	3.76	2.4	1.582	0.057
47	2.792	2.4	1.178	0.119
48	0.282	2.4	0.133	0.447
49	-0.032	2.4	0.002	0.499
50	-0.076	2.4	-0.016	0.493
51	8.568	2.4	3.585	0
52	11.527	2.4	4.818	0
53	14.348	2.4	5.993	0
54	15.964	2.4	6.667	0
55	19.43	2.4	8.111	0
56	4.16	2.198	1.907	0.028
57	3.176	2.198	1.459	0.072
58	1.732	2.198	0.802	0.211
59	0.77	2.198	0.364	0.358
60	0.251	2.198	0.128	0.449
61	-0.016	2.198	0.007	0.497
62	1.073	2.198	0.502	0.308
63	3.158	2.198	1.451	0.073
64	4.103	2.198	1.881	0.03
65	4.617	2.198	2.114	0.017
66	5.272	2.198	2.413	0.008
67	2.346	1.713	1.38	0.084
68	1.503	1.713	0.888	0.187
69	0.897	1.713	0.534	0.297
70	0.243	1.713	0.153	0.439
71	0.026	1.713	0.026	0.49
72	-0.027	1.713	-0.005	0.498
73	-0.05	1.713	-0.019	0.493
74	1.165	1.713	0.691	0.245
75	1.545	1.713	0.913	0.181
76	0.907	1.713	0.54	0.295
77	1.878	1.713	1.107	0.134
78	4.817	1.713	2.823	0.002
79	4	1.713	2.346	0.009
80	2.655	1.713	1.561	0.059
81	1.643	1.713	0.97	0.166
82	0.248	1.713	0.155	0.438
83	0.016	1.713	0.02	0.492
84	-0.162	1.713	-0.084	0.467
85	-1.034	1.713	-0.593	0.277
86	2.218	1.713	1.306	0.096
87	3.586	1.713	2.104	0.018
88	3.802	1.713	2.231	0.013

89	7.196	2.4	3.013	0.001
90	5.512	2.4	2.312	0.01
91	3.582	2.4	1.508	0.066
92	2.558	2.4	1.081	0.14
93	1.199	2.4	0.515	0.303
94	0.695	2.4	0.305	0.38
95	-0.142	2.4	-0.044	0.483
96	1.502	2.4	0.641	0.261
97	1.342	2.4	0.574	0.283
98	2.597	2.4	1.097	0.136
99	5.594	2.4	2.346	0.009
100	4.791	2.4	2.011	0.022
101	3.747	2.4	1.577	0.057
102	2.412	2.4	1.02	0.154
103	0.919	2.4	0.398	0.345
104	0.204	2.4	0.1	0.46
105	0.013	2.4	0.021	0.492
106	1.953	2.4	0.829	0.204
107	3.647	2.4	1.535	0.062
108	4.706	2.4	1.976	0.024
109	4.222	2.4	1.774	0.038
110	8.491	2.4	3.553	0
111	4.094	1.972	2.089	0.018
112	3.09	1.972	1.579	0.057
113	1.799	1.972	0.925	0.178
114	0.806	1.972	0.421	0.337
115	0.092	1.972	0.059	0.477
116	-0.073	1.972	-0.025	0.49
117	1.23	1.972	0.636	0.262
118	1.758	1.972	0.904	0.183
119	3.201	1.972	1.636	0.051
120	3.756	1.972	1.917	0.028
121	6.242	1.972	3.178	0.001
122	2.266	1.403	1.624	0.052
123	1.701	1.403	1.221	0.111
124	1.362	1.403	0.98	0.164
125	1.01	1.403	0.729	0.233
126	0.695	1.403	0.504	0.307
127	0.437	1.403	0.321	0.374
128	-0.124	1.403	-0.08	0.468
129	0.183	1.403	0.139	0.445
130	0.089	1.403	0.072	0.471
131	0.018	1.403	0.022	0.491
132	0.474	1.403	0.347	0.364
133	4.881	1.972	2.488	0.006
134	3.139	1.972	1.604	0.054
135	2.204	1.972	1.13	0.129
136	0.809	1.972	0.422	0.336
137	0.334	1.972	0.182	0.428
138	0.011	1.972	0.018	0.493
139	0.014	1.972	0.019	0.492
140	0.549	1.972	0.291	0.386
141	0.573	1.972	0.303	0.381

142	0.176	1.972	0.102	0.46
143	1.552	1.972	0.799	0.212
144	4.776	1.713	2.799	0.003
145	3.451	1.713	2.025	0.021
146	2.722	1.713	1.6	0.055
147	1.771	1.713	1.045	0.148
148	1.093	1.713	0.649	0.258
149	0.632	1.713	0.38	0.352
150	-0.112	1.713	-0.055	0.478
151	-0.279	1.713	-0.152	0.44
152	-0.173	1.713	-0.09	0.464
153	-0.755	1.713	-0.43	0.333
154	-0.031	1.713	-0.008	0.497
155	2.897	1.403	2.074	0.019
156	2.093	1.403	1.501	0.067
157	1.627	1.403	1.169	0.121
158	0.699	1.403	0.507	0.306
159	0.339	1.403	0.251	0.401
160	0.02	1.403	0.023	0.491
161	-0.223	1.403	-0.151	0.44
162	-0.236	1.403	-0.16	0.436
163	-0.197	1.403	-0.132	0.448
164	-0.757	1.403	-0.531	0.298
165	-0.028	1.403	-0.011	0.495

Notes: This table provides the Moran's I of local spatial autocorrelation. Ii is the value of local Moran's I, sd(Ii) is standard error of local Moran's I, z is z-stats.

Table A.108: Spatial Lag Model Test in OLS Regression (Model 1.1)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
s2	0.0102	0.0811	0.13	0.9	-0.1487	0.1691
s8	0.3361	0.2070	1.62	0.104	-0.0696	0.7418
s9	1.5645	0.0982	15.93	0	1.3721	1.7569
Dist1	1.65E-06	1.34E-06	1.22	0.221	-9.89E-07	4.28E-06
Dist3	-5.30E-06	1.05E-06	-5.05	0	-7.36E-06	-3.24E-06
_cons	-4.6319	0.9624	-4.81	0	-6.5182	-2.7456
rho	0.0115	0.0028	4.19	0	0.0061	0.0170
Wald test of rho=0	chi2(1) = 17.525					
	p-value = 0					
Likelihood ratio test of rho=0	chi2(1) = 16.655					
	p-value = 0					
Lagrange multiplier test of rho=0	chi2(1) = 15.885					
	p-value = 0					
Acceptable range for rho: -1.678 < rho < 1.000						

Notes: This table provides the spatial model test in OLS regression. The null hypotheses of Wald test and likelihood ratio test are that the model is homoscedastic. The null hypothesis of Lagrange multiplier test is that there is no spatially lagged dependent variable in the model.

Table A.109: Spatial Error Model Test in OLS Regression (Model 1.2)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
lag1_price	0.8748	0.0364	24.01	0	0.8034	0.9463
s2	0.1692	0.0898	1.88	0.06	-0.0068	0.3453
s8	-0.0527	0.1032	-0.51	0.609	-0.2549	0.1495
s9	0.0508	0.0981	0.52	0.605	-0.1415	0.2431
Dist1	1.28E-07	9.45E-07	0.14	0.892	-1.72E-06	1.98E-06
Dist3	-1.26E-06	8.37E-07	-1.5	0.133	-2.90E-06	3.84E-07
_cons	0.0038	0.0127	0.3	0.765	-0.0211	0.0287
lambda	0.1697	0.0208	8.17	0	0.1290	0.2105
Wald test of lambda=0	chi2(1) = 66.725					
	p-value = 0					
Likelihood ratio test of lambda=0	chi2(1) = 52.322					
	p-value = 0					
Lagrange multiplier test of lambda=0	chi2(1) = 48.828					
	p-value = 0					
Acceptable range for lambda: -1.678 < lambda < 1.000						

Notes: This table provides the spatial model test in OLS regression. The null hypotheses of Wald test and likelihood ratio test are that the model is homoscedastic. The null hypothesis of Lagrange multiplier test is that there is no spatially lagged error term in the model.

Table A.110: Spatial Lag Model Test in OLS Regression (Model 2.1)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
d1	1.5897	0.0978	16.26	0	1.3980	1.7814
d7	-0.0471	0.2432	-0.19	0.847	-0.5237	0.4295
d8	-12.0171	4.5765	-2.63	0.009	-20.9868	-3.0473
Dist1	1.60E-06	1.30E-06	1.23	0.218	-9.47E-07	4.15E-06
Dist3	-5.35E-06	1.02E-06	-5.27	0	-7.34E-06	-3.36E-06
_cons	-1.5512	1.3495	-1.15	0.25	-4.1961	1.0938
rho	0.0112	0.0027	4.19	0	0.0059	0.0164
Wald test of rho=0	chi2(1) = 17.515					
	p-value = 0					
Likelihood ratio test of rho=0	chi2(1) = 16.646					
	p-value = 0					
Lagrange multiplier test of rho=0	chi2(1) = 15.857					
	p-value = 0					
Acceptable range for rho: -1.678 < rho < 1.000						

Notes: This table provides the spatial model test in OLS regression. The null hypotheses of Wald test and likelihood ratio test are that the model is homoscedastic. The null hypothesis of Lagrange multiplier test is that there is no spatially lagged dependent variable in the model.

Table A.111: Spatial Error Model Test in OLS Regression (Model 2.2)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
lag1_price	0.8661	0.0369	23.45	0	0.7937	0.9385
d1	0.2117	0.1092	1.94	0.052	-0.0022	0.4257
d7	0.0449	0.0683	0.66	0.511	-0.0889	0.1787
d8	-6.5319	4.0305	-1.62	0.105	-14.4315	1.3677
Dist1	1.27E-07	9.24E-07	0.14	0.89	-1.68E-06	1.94E-06
Dist3	-1.30E-06	8.17E-07	-1.59	0.112	-2.90E-06	3.01E-07
_cons	0.0052	0.0139	0.38	0.705	-0.0219	0.0324
lambda	0.1631	0.0217	7.53	0	0.1207	0.2056
Wald test of lambda=0	chi2(1) = 56.645					
	p-value = 0					
Likelihood ratio test of lambda=0	chi2(1) = 45.959					
	p-value = 0					
Lagrange multiplier test of lambda=0	chi2(1) = 41.746					
	p-value = 0					
Acceptable range for lambda: -1.678 < lambda < 1.000						

Notes: This table provides the spatial model test in OLS regression. The null hypotheses of Wald test and likelihood ratio test are that the model is homoscedastic. The null hypothesis of Lagrange multiplier test is that there is no spatially lagged error term in the model.

Table A.112: Spatial Lag Model Test in OLS Regression (Model 3.1)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
d2	1.0655	0.0635	16.77	0	0.9409	1.1900
d8	-10.6515	3.6393	-2.93	0.003	-17.7844	-3.5186
Dist1	1.62E-06	1.32E-06	1.23	0.22	-9.64E-07	4.20E-06
Dist3	-5.33E-06	1.03E-06	-5.19	0	-7.35E-06	-3.32E-06
_cons	2.1824	0.2162	10.09	0	1.7586	2.6063
rho	0.0113	0.0027	4.18	0	0.0060	0.0166
Wald test of rho=0	chi2(1) = 17.493					
	p-value = 0					
Likelihood ratio test of rho=0	chi2(1) = 16.626					
	p-value = 0					
Lagrange multiplier test of rho=0	chi2(1) = 15.846					
	p-value = 0					
Acceptable range for rho: -1.678 < rho < 1.000						

Notes: This table provides the spatial model test in OLS regression. The null hypotheses of Wald test and likelihood ratio test are that the model is homoscedastic. The null hypothesis of Lagrange multiplier test is that there is no spatially lagged dependent variable in the model.

Table A.113: Spatial Error Model Test in OLS Regression (Model 3.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8270	0.0433	19.11	0	0.7422	0.9118
d2	0.2462	0.0564	4.37	0	0.1358	0.3567
d8	-6.2329	2.8276	-2.2	0.028	-11.7750	-0.6909
Dist1	7.16E-07	7.25E-07	0.99	0.323	-7.04E-07	2.14E-06
Dist3	-1.42E-06	6.30E-07	-2.25	0.025	-2.65E-06	-1.81E-07
_cons	0.5739	0.2382	2.41	0.016	0.1070	1.0408
lambda	0.0245	0.0156	1.57	0.116	-0.0061	0.0551
Wald test of lambda=0	chi2(1) = 2.465					
	p-value = 0.116					
Likelihood ratio test of lambda=0	chi2(1) = 7.238					
	p-value = 0.007					
Lagrange multiplier test of lambda=0	chi2(1) = 30.986					
	p-value = 0					
Acceptable range for lambda: -1.678 < lambda < 1.000						

Notes: This table provides the spatial model test in OLS regression. The null hypotheses of Wald test and likelihood ratio test are that the model is homoscedastic. The null hypothesis of Lagrange multiplier test is that there is no spatially lagged error term in the model.

Table A.114: Spatial Lag Model Test in OLS Regression (Model 4.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d4	7.3602	0.4559	16.14	0	6.4667	8.2537
d7	-0.0482	0.2442	-0.2	0.843	-0.5269	0.4305
d8	-9.1223	4.5677	-2	0.046	-18.0747	-0.1698
Dist1	1.61E-06	1.31E-06	1.23	0.219	-9.53E-07	4.16E-06
Dist3	-5.35E-06	1.02E-06	-5.24	0	-7.34E-06	-3.35E-06
_cons	-7.5977	1.5670	-4.85	0	-10.6690	-4.5263
rho	0.0112	0.0027	4.18	0	0.0060	0.0165
Wald test of rho=0	chi2(1) = 17.504					
	p-value = 0					
Likelihood ratio test of rho=0	chi2(1) = 16.636					
	p-value = 0					
Lagrange multiplier test of rho=0	chi2(1) = 15.85					
	p-value = 0					
Acceptable range for rho: -1.678 < rho < 1.000						

Notes: This table provides the spatial model test in OLS regression. The null hypotheses of Wald test and likelihood ratio test are that the model is homoscedastic. The null hypothesis of Lagrange multiplier test is that there is no spatially lagged dependent variable in the model.

Table A.115: Spatial Error Model Test in OLS Regression (Model 4.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8421	0.0418	20.13	0	0.7601	0.9241
d4	1.5461	0.3993	3.87	0	0.7635	2.3287
d7	0.1614	0.1297	1.24	0.213	-0.0928	0.4157
d8	-4.7237	2.4272	-1.95	0.052	-9.4810	0.0335
Dist1	1.74E-07	7.09E-07	0.25	0.806	-1.22E-06	1.56E-06
Dist3	-1.74E-06	5.64E-07	-3.08	0.002	-2.84E-06	-6.34E-07
_cons	-2.2013	0.9162	-2.4	0.016	-3.9971	-0.4054
lambda	-0.0008	0.0028	-0.27	0.784	-0.0063	0.0047
Wald test of lambda=0	chi2(1) = 0.075					
	p-value = 0.784					
Likelihood ratio test of lambda=0	chi2(1) = 0.069					
	p-value = 0.792					
Lagrange multiplier test of lambda=0	chi2(1) = 42.682					
	p-value = 0					
Acceptable range for lambda: -1.678 < lambda < 1.000						

Notes: This table provides the spatial model test in OLS regression. The null hypotheses of Wald test and likelihood ratio test are that the model is homoscedastic. The null hypothesis of Lagrange multiplier test is that there is no spatially lagged error term in the model.

Table A.116: Results of Hausman Test in Panel Model (Model 1.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
s2	0.0105	0.0592	0.18	0.86	-0.1065	0.1274
s8	0.3531	0.1510	2.34	0.021	0.0546	0.6516
s9	1.6486	0.0701	23.51	0	1.5099	1.7872
Dist1	2.38E-07	4.36E-06	0.05	0.956	-8.37E-06	8.85E-06
Dist3	-6.79E-06	3.31E-06	-2.05	0.042	-1.3E-05	-2.51E-07
_cons	-4.7878	0.7142	-6.7	0	-6.1994	-3.3763
Hausman LM Test = 0.21 P-Value > Chi2(3) 1.0000						

Notes: This table provides results of the Hausman test. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.117: Test Results for SAC Model (Model 1.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
s2	0.0127	0.0895	0.14	0.887	-0.1627	0.1881
s8	0.3132	0.2237	1.4	0.162	-0.1253	0.7516
s9	1.3673	0.1154	11.85	0	1.1411	1.5936
Dist1	1.22E-06	1.39E-06	0.88	0.38	-1.50E-06	3.94E-06
Dist3	-5.30E-06	1.11E-06	-4.79	0	-7.47E-06	-3.13E-06
_cons	-3.6888	1.0072	-3.66	0	-5.6628	-1.7147
/Rho	0.0390	0.0102	3.82	0	0.0190	0.0590
/Lambda	0.0284	0.0116	2.44	0.015	0.0055	0.0512
/Sigma	0.1944	0.0107	18.14	0	0.1734	0.2154
LR Test (Rho=0): 14.5798 P-Value > Chi2(1) 0.0001						
LR Test (Lambda=0): 5.9377 P-Value > Chi2(1) 0.0148						
LR Test SAC vs. OLS (Rho+Lambda=0): 15.1605 P-Value > Chi2(2) 0.0005						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	0.127					
Wooldridge LM	0.587					
p-value	0.443					
Breusch-Pagan	92					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.118: Test Results for SAR Model (Model 1.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
s2	0.0102	0.0811	0.13	0.9	-0.1487	0.1691
s8	0.3362	0.2070	1.62	0.104	-0.0696	0.7419
s9	1.5649	0.0982	15.94	0	1.3725	1.7574
Dist1	1.64E-06	1.34E-06	1.22	0.223	-9.96E-07	4.27E-06
Dist3	-5.31E-06	1.05E-06	-5.06	0	-7.37E-06	-3.25E-06
_cons	-4.6327	0.9624	-4.81	0	-6.5190	-2.7464
/Rho	0.0115	0.0028	4.18	0	0.0061	0.0169
/Sigma	0.1998	0.0110	18.17	0	0.1783	0.2214
LR Test SAR vs. OLS (Rho=0): 17.4363 P-Value > Chi2(1) 0.0000						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	0.091					
Wooldridge LM	0.587					
p-value	0.443					
Breusch-Pagan	81.02					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.119: Test Results for SEM Model (Model 1.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
s2	0.0145	0.0798	0.18	0.856	-0.1420	0.1709
s8	0.3881	0.1991	1.95	0.051	-0.0021	0.7783
s9	1.6635	0.0934	17.82	0	1.4805	1.8464
Dist1	1.57E-06	1.37E-06	1.15	0.25	-1.11E-06	4.25E-06
Dist3	-5.81E-06	1.03E-06	-5.64	0	-7.82E-06	-3.79E-06
_cons	-5.1862	0.9225	-5.62	0	-6.9943	-3.3781
/Lambda	-0.0074	0.0025	-2.96	0.003	-0.0123	-0.0025
/Sigma	0.2035	0.0112	18.17	0	0.1815	0.2254
LR Test SEM vs. OLS (Lambda=0): 8.7369 P-Value > Chi2(1) 0.0031						
Acceptable Range for Lambda: -0.4134 < Lambda < 0.2020						
AIC	0.064					
Wooldridge LM	0.587					
p-value	0.443					
Breusch-Pagan	70.11					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.120: Test Results for SDM Model (Model 1.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
s2	0.0270	0.2034	0.13	0.894	-0.3715	0.4256
s8	0.2482	0.3154	0.79	0.431	-0.3700	0.8664
s9	1.3093	0.2038	6.42	0	0.9098	1.7088
Dist1	-1.28E-06	3.63E-06	-0.35	0.725	-8.39E-06	5.84E-06
Dist3	-2.64E-06	3.17E-06	-0.83	0.406	-8.85E-06	3.58E-06
w1x_s2	-0.0043	0.0441	-0.1	0.922	-0.0907	0.0821
w1x_s8	-0.0025	0.0546	-0.05	0.963	-0.1095	0.1045
w1x_s9	-0.0543	0.0548	-0.99	0.322	-0.1618	0.0532
w1x_Dist1	5.41E-07	1.37E-06	0.4	0.692	-2.13E-06	3.22E-06
w1x_Dist3	-5.34E-07	1.09E-06	-0.49	0.626	-2.68E-06	1.61E-06
_cons	-3.1431	1.0369	-3.03	0.002	-5.1753	-1.1108
/Rho	0.0784	0.0221	3.54	0	0.0350	0.1218
/Sigma	0.1908	0.0107	17.91	0	0.1699	0.2117
LR Test SDM vs. OLS (Rho=0): 12.5398 P-Value > Chi2(1) 0.0004						
LR Test (wX's =0): 11.7681 P-Value > Chi2(5) 0.0381						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	2.425					
Wooldridge LM	0.773					
p-value	0.379					
Breusch-Pagan	152.3					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.121: Results of Hausman Test in Panel Model (Model 1.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8966	0.0410	21.84	0	0.8154	0.9777
s2	0.0882	0.0436	2.02	0.045	0.0020	0.1744
s8	-0.2340	0.1142	-2.05	0.042	-0.4597	-0.0084
s9	0.0685	0.0888	0.77	0.442	-0.1071	0.2440
Dist1	1.07E-07	6.98E-07	0.15	0.879	-1.27E-06	1.49E-06
Dist3	-1.46E-06	5.83E-07	-2.5	0.013	-2.61E-06	-3.08E-07
_cons	0.7029	0.5736	1.23	0.222	-0.4309	1.8366
Hausman LM Test = 4.73199 P-Value > Chi2(4) 0.3159						

Notes: This table provides results of the Hausman test. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.122: Test Results for SEM Model (Model 1.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8875	0.0372	23.86	0	0.8145	0.9604
s2	0.0897	0.0438	2.05	0.041	0.0038	0.1756
s8	-0.2677	0.0542	-4.94	0	-0.3739	-0.1615
s9	0.0699	0.0655	1.07	0.285	-0.0584	0.1982
Dist1	5.52E-07	7.17E-07	0.77	0.441	-8.54E-07	1.96E-06
Dist3	-1.16E-06	5.84E-07	-1.99	0.047	-2.30E-06	-1.55E-08
/Lambda	0.0154	0.0063	2.44	0.015	0.0030	0.0278
/Sigma	0.1031	0.0057	18.16	0	0.0920	0.1142
LR Test SEM vs. OLS (Lambda=0): 5.9482 P-Value > Chi2(1) 0.0147						
Acceptable Range for Lambda: -0.4134 < Lambda < 0.2020						
AIC	0.014					
Wooldridge LM	9.05					
p-value	0.37					
Breusch-Pagan	16.7					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.123: Test Results for SDM Model (Model 1.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8803	0.0377	23.37	0	0.8065	0.9542
s2	0.1676	0.0984	1.7	0.089	-0.0253	0.3605
s8	-0.1213	0.1826	-0.66	0.506	-0.4791	0.2365
s9	0.0023	0.1126	0.02	0.984	-0.2185	0.2231
Dist1	-1.48E-07	1.74E-06	-0.09	0.932	-3.56E-06	3.26E-06
Dist3	-9.20E-07	1.52E-06	-0.61	0.544	-3.90E-06	2.06E-06
w1x_lag1_price	-0.0923	0.0235	-3.93	0	-0.1384	-0.0463
w1x_s2	-0.0268	0.0217	-1.23	0.219	-0.0694	0.0159
w1x_s8	0.0014	0.0285	0.05	0.961	-0.0546	0.0573
w1x_s9	-0.0005	0.0369	-0.01	0.989	-0.0729	0.0718
w1x_Dist1	-5.82E-08	6.54E-07	-0.09	0.929	-1.34E-06	1.22E-06
w1x_Dist3	1.09E-08	5.24E-07	0.02	0.983	-1.02E-06	1.04E-06
_cons	0.4403	0.6911	0.64	0.524	-0.9142	1.7948
/Rho	0.1116	0.0163	6.86	0	0.0798	0.1435
/Sigma	0.0909	0.0051	17.76	0	0.0808	0.1009
LR Test SDM vs. OLS (Rho=0): 47.0839 P-Value > Chi2(1) 0.0000						
LR Test (wX's =0): 47.7953 P-Value > Chi2(6) 0.0000						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	4.96					
Wooldridge LM	5.98					
p-value	0.14					
Breusch-Pagan	159.4					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.124: Results of Hausman Test in Panel Model (Model 2.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d1	1.6718	0.0667	25.08	0	1.5401	1.8036
d7	-0.0509	0.1692	-0.3	0.764	-0.3853	0.2835
d8	-12.6387	3.1826	-3.97	0	-18.9291	-6.3484
Dist1	2.38E-07	4.36E-06	0.05	0.956	-8.37E-06	8.85E-06
Dist3	-6.79E-06	3.31E-06	-2.05	0.042	-1.3E-05	-2.51E-07
_cons	-1.5389	0.9483	-1.62	0.107	-3.4132	0.3355
Hausman LM Test = 0.00000 P-Value > Chi2(3) 1.0000						

Notes: This table provides results of the Hausman test. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.125: Test Results for SAR Model (Model 2.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d1	1.5901	0.0978	16.26	0	1.3984	1.7817
d7	-0.0471	0.2432	-0.19	0.846	-0.5237	0.4295
d8	-12.0201	4.5765	-2.63	0.009	-20.9898	-3.0503
Dist1	1.59E-06	1.30E-06	1.23	0.22	-9.53E-07	4.14E-06
Dist3	-5.36E-06	1.02E-06	-5.28	0	-7.35E-06	-3.37E-06
_cons	-1.5511	1.3495	-1.15	0.25	-4.1961	1.0939
/Rho	0.0111	0.0027	4.18	0	0.0059	0.0163
/Sigma	0.1931	0.0106	18.17	0	0.1723	0.2140
LR Test SAR vs. OLS (Rho=0): 17.4324 P-Value > Chi2(1) 0.0000						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	0.085					
Wooldridge LM	3.02					
p-value	0.08					
Breusch-Pagan	92.14					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.126: Test Results for SDM Model (Model 2.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d1	1.3859	0.2277	6.09	0	0.9396	1.8322
d7	0.0578	0.2828	0.2	0.838	-0.4965	0.6120
d8	-11.3819	9.8538	-1.16	0.248	-30.6950	7.9311
Dist1	-1.08E-06	3.58E-06	-0.3	0.763	-8.10E-06	5.94E-06
Dist3	-2.79E-06	3.13E-06	-0.89	0.374	-8.92E-06	3.35E-06
w1x_d1	-0.0343	0.0693	-0.5	0.62	-0.1701	0.1015
w1x_d7	-0.0207	0.0368	-0.56	0.574	-0.0929	0.0515
w1x_d8	0.4725	2.1156	0.22	0.823	-3.6741	4.6190
w1x_Dist1	4.81E-07	1.35E-06	0.36	0.721	-2.16E-06	3.12E-06
w1x_Dist3	-6.33E-07	1.08E-06	-0.58	0.559	-2.75E-06	1.49E-06
_cons	-1.1692	1.3314	-0.88	0.38	-3.7786	1.4402
/Rho	0.0588	0.0262	2.24	0.025	0.0074	0.1102
/Sigma	0.1883	0.0105	17.99	0	0.1678	0.2088
LR Test SDM vs. OLS (Rho=0): 5.0220 P-Value > Chi2(1) 0.0250						
LR Test (wX's =0): 6.1921 P-Value > Chi2(5) 0.2880						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	1.38					
Wooldridge LM	6.08					
p-value	0.01					
Breusch-Pagan	149.2					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.127: Results of Hausman Test in Panel Model (Model 2.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8435	0.0395	21.36	0	0.7655	0.9216
d1	0.3313	0.0816	4.06	0	0.1700	0.4927
d7	0.1554	0.1329	1.17	0.244	-0.1073	0.4181
d8	-5.4230	2.5159	-2.16	0.033	-10.3959	-0.4500
Dist1	1.14E-07	6.86E-07	0.17	0.868	-1.24E-06	1.47E-06
Dist3	-1.78E-06	5.71E-07	-3.11	0.002	-2.90E-06	-6.47E-07
_cons	-0.8855	0.7362	-1.2	0.231	-2.3406	0.5697
Hausman LM Test = 16.14301 P-Value > Chi2(4) 0.0028						

Notes: This table provides results of the Hausman test. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.128: Test Results for SEM Model (Model 2.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8638	0.0375	23.06	0	0.7904	0.9372
d1	0.2432	0.0897	2.71	0.007	0.0673	0.4190
d7	0.0194	0.0526	0.37	0.711	-0.0836	0.1224
d8	-6.9021	2.9899	-2.31	0.021	-12.7623	-1.0420
Dist1	1.94E-07	7.91E-07	0.25	0.806	-1.36E-06	1.74E-06
Dist3	-1.42E-06	6.79E-07	-2.09	0.037	-2.75E-06	-8.52E-08
_cons	0.0198	0.0301	0.66	0.511	-0.0393	0.0789
/Lambda	0.1084	0.0167	6.48	0	0.0756	0.1412
/Sigma	0.0912	0.0051	17.78	0	0.0811	0.1012
LR Test SEM vs. OLS (Lambda=0): 41.9385 P-Value > Chi2(1) 0.0000						
Acceptable Range for Lambda: -0.4134 < Lambda < 0.2020						
AIC	0.012					
Wooldridge LM	13.2					
p-value	0					
Breusch-Pagan	27					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.129: Test Results for SDM Model (Model 2.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8651	0.0376	22.98	0	0.7914	0.9389
d1	0.1892	0.1234	1.53	0.125	-0.0525	0.4310
d7	0.1864	0.1391	1.34	0.18	-0.0862	0.4589
d8	-4.5961	4.7869	-0.96	0.337	-13.9784	4.7861
Dist1	1.75E-07	1.74E-06	0.1	0.92	-3.24E-06	3.59E-06
Dist3	-1.23E-06	1.52E-06	-0.81	0.419	-4.20E-06	1.75E-06
w1x_lag1_price	-0.1119	0.0217	-5.15	0	-0.1544	-0.0693
w1x_d1	0.0397	0.0468	0.85	0.397	-0.0521	0.1315
w1x_d7	-0.0265	0.0203	-1.3	0.192	-0.0664	0.0134
w1x_d8	0.1562	1.0553	0.15	0.882	-1.9121	2.2246
w1x_Dist1	-1.46E-07	6.54E-07	-0.22	0.823	-1.43E-06	1.13E-06
w1x_Dist3	-1.48E-07	5.27E-07	-0.28	0.779	-1.18E-06	8.85E-07
_cons	-0.6182	0.6476	-0.95	0.34	-1.8874	0.6511
/Rho	0.0979	0.0186	5.28	0	0.0615	0.1342
/Sigma	0.0909	0.0051	17.83	0	0.0809	0.1009
LR Test SDM vs. OLS (Rho=0): 27.8260 P-Value > Chi2(1) 0.0000						
LR Test (wX's =0): 39.5374 P-Value > Chi2(6) 0.0000						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	3.81					
Wooldridge LM	8.16					
p-value	0					
Breusch-Pagan	159					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.130: Results of Hausman Test in Panel Model (Model 3.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d2	1.1214	0.0440	25.47	0	1.0344	1.2084
d8	-11.1940	2.5784	-4.34	0	-16.2898	-6.0983
Dist1	2.38E-07	4.15E-06	0.06	0.954	-7.96E-06	8.43E-06
Dist3	-6.79E-06	3.15E-06	-2.16	0.033	-1.3E-05	-5.67E-07
_cons	2.3829	0.1956	12.19	0	1.9964	2.7693
Hausman LM Test = -0.00000 P-Value > Chi2(2) 1.0000						

Notes: This table provides results of the Hausman test. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.131: Test Results for SAC Model (Model 3.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d2	1.0928	0.0677	16.48	0	0.9829	1.2482
d8	-11.1203	3.8599	-2.88	0.004	-18.6855	-3.5551
Dist1	1.68E-06	1.37E-06	1.23	0.22	-1.01E-06	4.36E-06
Dist3	-5.42E-06	1.05E-06	-5.15	0	-7.48E-06	-3.36E-06
_cons	2.1740	0.2371	9.17	0	1.7093	2.6386
/Rho	0.0060	0.0173	0.35	0.729	-0.0280	0.0400
/Lambda	0.0092	0.0307	0.3	0.764	-0.0510	0.0694
/Sigma	0.1956	0.0108	18.15	0	0.1745	0.2168
LR Test (Rho=0): 0.1200 P-Value > Chi2(1) 0.7290						
LR Test (Lambda=0): 0.0898 P-Value > Chi2(1) 0.7645						
LR Test SAC vs. OLS (Rho+Lambda=0): 16.0048 P-Value > Chi2(2) 0.0003						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	0.081					
Wooldridge LM	4.32					
p-value	0.04					
Breusch-Pagan	95.5					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.132: Test Results for SAR Model (Model 3.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d2	1.0658	0.0635	16.78	0	0.9412	1.1903
d8	-10.6541	3.6393	-2.93	0.003	-17.7870	-3.5213
Dist1	1.61E-06	1.32E-06	1.22	0.221	-9.70E-07	4.19E-06
Dist3	-5.34E-06	1.03E-06	-5.19	0	-7.36E-06	-3.33E-06
_cons	2.1834	0.2162	10.1	0	1.7597	2.6072
/Rho	0.0112	0.0027	4.17	0	0.0060	0.0165
/Sigma	0.1957	0.0108	18.17	0	0.1745	0.2168
LR Test SAR vs. OLS (Rho=0): 17.4088 P-Value > Chi2(1) 0.0000						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	0.086					
Wooldridge LM	4.32					
p-value	0.04					
Breusch-Pagan	97.34					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.133: Test Results for SEM Model (Model 3.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d2	1.1156	0.0677	16.48	0	0.9829	1.2482
d8	-10.7029	4.0077	-2.67	0.008	-18.5577	-2.8480
Dist1	1.75E-06	1.37E-06	1.28	0.201	-9.35E-07	4.44E-06
Dist3	-5.43E-06	1.08E-06	-5.04	0	-7.54E-06	-3.32E-06
_cons	2.1127	0.2407	8.78	0	1.6409	2.5844
/Lambda	0.0198	0.0053	3.71	0	0.0094	0.0303
/Sigma	0.1954	0.0108	18.17	0	0.1743	0.2165
LR Test SEM vs. OLS (Lambda=0): 13.7911 P-Value > Chi2(1) 0.0002						
Acceptable Range for Lambda: -0.4134 < Lambda < 0.2020						
AIC	0.072					
Wooldridge LM	4.32					
p-value	0.04					
Breusch-Pagan	91.58					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.134: Test Results for SDM Model (Model 3.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d2	0.9414	0.1658	5.68	0	0.6165	1.2663
d8	-1.4903	7.2158	-0.21	0.836	-15.6330	12.6524
Dist1	-3.48E-07	3.61E-06	-0.1	0.923	-7.42E-06	6.72E-06
Dist3	-3.08E-06	3.18E-06	-0.97	0.332	-9.31E-06	3.14E-06
w1x_d2	-0.0183	0.0489	-0.37	0.708	-0.1141	0.0775
w1x_d8	-1.6873	1.3816	-1.22	0.222	-4.3952	1.0206
w1x_Dist1	1.55E-08	1.34E-06	0.01	0.991	-2.60E-06	2.63E-06
w1x_Dist3	-5.98E-07	1.10E-06	-0.54	0.587	-2.76E-06	1.56E-06
_cons	1.8793	0.3244	5.79	0	1.2435	2.5150
/Rho	0.0522	0.0239	2.18	0.029	0.0053	0.0990
/Sigma	0.1916	0.0106	18.06	0	0.1708	0.2124
LR Test SDM vs. OLS (Rho=0): 4.7618 P-Value > Chi2(1) 0.0291						
LR Test (wX's =0): 5.2007 P-Value > Chi2(4) 0.2673						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	1.07					
Wooldridge LM	5.36					
p-value	0.02					
Breusch-Pagan	147.1					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.135: Results of Hausman Test in Panel Model (Model 3.2)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
lag1_price	0.8245	0.0369	22.36	0	0.7516	0.8974
d2	0.2483	0.0509	4.88	0	0.1476	0.3489
d8	-7.6861	1.9204	-4	0	-11.4816	-3.8905
Dist1	1.17E-07	6.71E-07	0.17	0.862	-1.21E-06	1.44E-06
Dist3	-1.89E-06	5.54E-07	-3.41	0.001	-2.98E-06	-7.93E-07
_cons	0.7617	0.1326	5.75	0	0.4997	1.0237
Hausman LM Test = 20.88812 P-Value > Chi2(3) 0.0001						

Notes: This table provides results of the Hausman test. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.136: Test Results for SEM Model (Model 3.2)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
lag1_price	0.8235	0.0399	20.64	0	0.7453	0.9017
d2	0.2494	0.0539	4.63	0	0.1438	0.3551
d8	-6.5869	2.3830	-2.76	0.006	-11.2575	-1.9162
Dist1	6.66E-07	7.06E-07	0.94	0.346	-7.19E-07	2.05E-06
Dist3	-1.47E-06	5.98E-07	-2.45	0.014	-2.64E-06	-2.96E-07
_cons	0.6103	0.1871	3.26	0.001	0.2436	0.9770
/Lambda	0.0218	0.0114	1.91	0.056	-0.0005	0.0440
/Sigma	0.0989	0.0054	18.16	0	0.0882	0.1096
LR Test SEM vs. OLS (Lambda=0): 3.6648 P-Value > Chi2(1) 0.0556						
Acceptable Range for Lambda: -0.4134 < Lambda < 0.2020						
AIC	0.014					
Wooldridge LM	24.82					
p-value	0					
Breusch-Pagan	19.62					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.137: Test Results for SDM Model (Model 3.2)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
lag1_price	0.8665	0.0367	23.59	0	0.7945	0.9385
d2	0.1156	0.0872	1.33	0.185	-0.0554	0.2866
d8	-5.7888	3.5679	-1.62	0.105	-12.7818	1.2041
Dist1	2.91E-07	1.71E-06	0.17	0.865	-3.06E-06	3.64E-06
Dist3	-1.29E-06	1.51E-06	-0.85	0.394	-4.24E-06	1.67E-06
w1x_lag1_price	-0.1045	0.0190	-5.51	0	-0.1417	-0.0674
w1x_d2	0.0371	0.0272	1.37	0.172	-0.0161	0.0904
w1x_d8	0.1072	0.6833	0.16	0.875	-1.2321	1.4466
w1x_Dist1	-2.03E-07	6.34E-07	-0.32	0.749	-1.44E-06	1.04E-06
w1x_Dist3	-1.83E-07	5.24E-07	-0.35	0.727	-1.21E-06	8.44E-07
_cons	0.7270	0.1791	4.06	0	0.3759	1.0780
/Rho	0.0840	0.0193	4.36	0	0.0462	0.1217
/Sigma	0.0908	0.0051	17.93	0	0.0809	0.1007
LR Test SDM vs. OLS (Rho=0): 19.0015 P-Value > Chi2(1) 0.0000						
LR Test (wX's =0): 32.8753 P-Value > Chi2(5) 0.0000						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	2.74					
Wooldridge LM	23.18					
p-value	0					
Breusch-Pagan	158.3					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.138: Results of Hausman Test in Panel Model (Model 4.1)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
d4	7.7421	0.3127	24.76	0	7.1240	8.3603
d7	-0.0521	0.1710	-0.3	0.761	-0.3901	0.2858
d8	-9.5965	3.1972	-3	0.003	-15.9156	-3.2774
Dist1	2.38E-07	4.36E-06	0.05	0.956	-8.37E-06	8.85E-06
Dist3	-6.79E-06	3.31E-06	-2.05	0.042	-1.3E-05	-2.51E-07
_cons	-7.8993	1.1041	-7.15	0	-10.0815	-5.7172
Hausman LM Test = -0.00000 P-Value > Chi2(3) 1.0000						

Notes: This table provides results of the Hausman test. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.139: Test Results for SAR Model (Model 4.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d4	7.3621	0.4558	16.15	0	6.4686	8.2555
d7	-0.0482	0.2442	-0.2	0.843	-0.5269	0.4304
d8	-9.1246	4.5676	-2	0.046	-18.0770	-0.1721
Dist1	1.60E-06	1.30E-06	1.22	0.221	-9.59E-07	4.16E-06
Dist3	-5.35E-06	1.02E-06	-5.25	0	-7.35E-06	-3.35E-06
_cons	-7.5992	1.5670	-4.85	0	-10.6705	-4.5278
/Rho	0.0112	0.0027	4.17	0	0.0059	0.0164
/Sigma	0.1940	0.0107	18.17	0	0.1730	0.2149
LR Test SAR vs. OLS (Rho=0): 17.4204 P-Value > Chi2(1) 0.0000						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	0.086					
Wooldridge LM	2.85					
p-value	0.09					
Breusch-Pagan	92.1					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.140: Test Results for SDM Model (Model 4.1)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
d4	6.2721	0.9438	6.65	0	4.4224	8.1219
d7	-0.0163	0.3732	-0.04	0.965	-0.7478	0.7153
d8	-9.4287	10.6359	-0.89	0.375	-30.2746	11.4172
Dist1	-1.10E-06	3.59E-06	-0.3	0.761	-8.14E-06	5.95E-06
Dist3	-2.78E-06	3.14E-06	-0.88	0.376	-8.93E-06	3.37E-06
w1x_d4	-0.1307	0.2665	-0.49	0.624	-0.6530	0.3917
w1x_d7	-0.0035	0.0685	-0.05	0.959	-0.1378	0.1308
w1x_d8	0.5507	2.3212	0.24	0.812	-3.9988	5.1002
w1x_Dist1	4.87E-07	1.35E-06	0.36	0.719	-2.16E-06	3.14E-06
w1x_Dist3	-6.30E-07	1.08E-06	-0.58	0.561	-2.76E-06	1.50E-06
_cons	-5.8585	1.7551	-3.34	0.001	-9.2985	-2.4185
/Rho	0.0595	0.0249	2.39	0.017	0.0106	0.1084
/Sigma	0.1888	0.0105	18	0	0.1683	0.2094
LR Test SDM vs. OLS (Rho=0): 5.6906 P-Value > Chi2(1) 0.0171						
LR Test (wX's =0): 6.6040 P-Value > Chi2(5) 0.2518						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	1.41					
Wooldridge LM	4.86					
p-value	0.03					
Breusch-Pagan	149.1					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.141: Results of Hausman Test in Panel Model (Model 4.2)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
lag1_price	0.8465	0.0395	21.42	0	0.7684	0.9247
d4	1.5022	0.3794	3.96	0	0.7524	2.2521
d7	0.1542	0.1332	1.16	0.249	-0.1091	0.4175
d8	-4.7888	2.4942	-1.92	0.057	-9.7187	0.1412
Dist1	1.14E-07	6.87E-07	0.17	0.869	-1.24E-06	1.47E-06
Dist3	-1.76E-06	5.72E-07	-3.07	0.003	-2.89E-06	-6.27E-07
_cons	-2.1026	0.8936	-2.35	0.02	-3.8687	-0.3364
Hausman LM Test = 15.06596 P-Value > Chi2(4) 0.0046						

Notes: This table provides results of the Hausman test. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.142: Test Results for SEM Model (Model 4.2)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
lag1_price	0.8421	0.0418	20.13	0	0.7601	0.9241
d4	1.5459	0.3993	3.87	0	0.7633	2.3285
d7	0.1614	0.1297	1.24	0.213	-0.0929	0.4157
d8	-4.7239	2.4274	-1.95	0.052	-9.4814	0.0336
Dist1	1.74E-07	7.09E-07	0.25	0.806	-1.22E-06	1.56E-06
Dist3	-1.74E-06	5.64E-07	-3.08	0.002	-2.84E-06	-6.34E-07
_cons	-2.2009	0.9164	-2.4	0.016	-3.9970	-0.4047
/Lambda	-0.0008	0.0028	-0.27	0.785	-0.0063	0.0047
/Sigma	0.1032	0.0057	18.17	0	0.0921	0.1144
LR Test SEM vs. OLS (Lambda=0): 0.0747 P-Value > Chi2(1) 0.7847						
Acceptable Range for Lambda: -0.4134 < Lambda < 0.2020						
AIC	0.012					
Wooldridge LM	13.8					
p-value	0					
Breusch-Pagan	25.8					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.143: Test Results for SDM Model (Model 4.2)

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
lag1_price	0.8668	0.0375	23.1	0	0.7933	0.9404
d4	0.9179	0.5083	1.81	0.071	-0.0784	1.9141
d7	0.2817	0.1995	1.41	0.158	-0.1093	0.6726
d8	-2.8803	5.2263	-0.55	0.582	-13.1237	7.3631
Dist1	1.75E-07	1.74E-06	0.1	0.92	-3.23E-06	3.58E-06
Dist3	-1.21E-06	1.52E-06	-0.8	0.424	-4.19E-06	1.76E-06
w1x_lag1_price	-0.1118	0.0212	-5.28	0	-0.1533	-0.0703
w1x_d4	0.1560	0.1696	0.92	0.358	-0.1763	0.4884
w1x_d7	-0.0488	0.0407	-1.2	0.23	-0.1286	0.0309
w1x_d8	-0.0721	1.1640	-0.06	0.951	-2.3534	2.2093
w1x_Dist1	-1.52E-07	6.54E-07	-0.23	0.816	-1.43E-06	1.13E-06
w1x_Dist3	-1.36E-07	5.25E-07	-0.26	0.795	-1.17E-06	8.94E-07
_cons	-1.8984	0.9666	-1.96	0.05	-3.7929	-0.0038
/Rho	0.0995	0.0178	5.58	0	0.0646	0.1345
/Sigma	0.0909	0.0051	17.83	0	0.0809	0.1009
LR Test SDM vs. OLS (Rho=0): 31.1807 P-Value > Chi2(1) 0.0000						
LR Test (wX's =0): 40.4785 P-Value > Chi2(6) 0.0000						
Acceptable Range for Rho: -0.4134 < Rho < 0.2020						
AIC	3.94					
Wooldridge LM	9.37					
p-value	0					
Breusch-Pagan	158.9					
p-value	0					

Notes: This table provides the spatial analysis test in panel model. The null hypothesis of LR Test (Lambda=0) is that there is no spatially lagged error term in the model. The null hypothesis of LR Test (Rho=0) is that there is no spatially lagged dependent variable in the model. AIC is Akaike Information Criterion. The null hypothesis is that there is no first-order autocorrelation in the model. The null hypothesis of Breusch-Pagan test is that there is a constant variance in the model.

Table A.144 – Table A.159 are belonging to **Chapter 6 The Uncertainty of House Prices and Real Options in China**

Table A.144: Variable List

Name	Variables	Unit
price	Average house prices	yuan
Landprice	Average land prices	yuan
GDP	Gross regional product	100 million yuan
CPI	Consumer price index	preceding year=100
une_r	Unemployment rate in urban area	%
pop_den	Population density of urban area	person/sq.km
num_edu	Number of regular institutions of higher education	unit
num_heal	Number of health care institutions	unit
num_lib	Number of institutions in public libraries	unit
num_muse	Number of museums	unit
size_building	Floor space of residential buildings completed	10000 sq.m

Notes: All variables were downloaded from the National Bureau of Statistics of China (NBS) website. Data is from 2000 to 2015.

Table A.145: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
price	496	3,722.77	3,029.72	854	22300
GDP	496	11,336.02	12,327.25	117.8	72812.55
CPI	496	102.34	2.13	96.7	110.1
une_r	496	3.60	0.71	0.8	6.5
pop_den	496	2,275.10	1,411.93	171	6307
num_edu	496	64.25	36.08	3	162
num_heal	496	19,014.57	18,239.52	1237	81403
num_lib	496	92.28	43.92	1	203
num_muse	496	71.67	56.00	1	312
size_building	496	5,041.41	3,784.01	33.4	20477.12
VIF	4.38				

Notes: This table summarises descriptive statistics (number of observations, sample mean, standard deviation, minimum and maximum) of the full sample of variables. VIF stands for variance inflation factor.

Table A.146: Code of Regions

Region	**ID**	**Region**	**ID**
Anhui	1	Jilin	17
Beijing	2	Liaoning	18
Chongqing	3	Nei Mongol	19
Fujian	4	Ningxia Hui	20
Gansu	5	Qinghai	21
Guangdong	6	Shaanxi	22
Guangxi	7	Shandong	23
Guizhou	8	Shanghai	24
Hainan	9	Shanxi	25
Hebei	10	Sichuan	26
Heilongjiang	11	Tianjin	27
Henan	12	Xinjiang Uygur	28
Hubei	13	Xizang	29
Hunan	14	Yunnan	30
Jiangsu	15	Zhejiang	31
Jiangxi	16		

Notes: This table provides the code of regions in the investigation of shape files.

Table A.147: Results of Hausman Test in Panel Model

	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
GDP	0.8153	0.0290	28.11	0	0.7583	0.8723
CPI	0.1167	0.3967	0.29	0.769	-0.6628	0.8962
une_r	-0.3213	0.0598	-5.37	0	-0.4388	-0.2038
pop_den	0.0060	0.0143	0.42	0.676	-0.0221	0.0340
num_edu	-0.1394	0.0506	-2.76	0.006	-0.2388	-0.0401
num_heal	0.0152	0.0189	0.8	0.421	-0.0220	0.0524
num_lib	-0.1918	0.0230	-8.34	0	-0.2370	-0.1467
num_muse	-0.0773	0.0257	-3.01	0.003	-0.1278	-0.0268
size_building	-0.1076	0.0207	-5.2	0	-0.1482	-0.0669
_cons	1.3391	0.7928	1.69	0.092	-0.2188	2.8971
Hausman LM Test = 334.95985 P-Value > Chi2(9) 0.0000						

Notes: This table provides results of the Hausman test. b=consistent under null hypothesis and alternative hypothesis. B=inconsistent under alternative hypothesis, efficient under null hypothesis. The null hypothesis is that difference in coefficients not systematic, which means random effect is appropriate.

Table A.148: Test Results for Choosing Between Spatial and Non-spatial Models

	Spatial fixed effect	Time-period fixed effect	Spatial and time-period fixed effect
LM spatial lag (classic)	46.93	22.93	34.8
	[0.000]	[0.000]	[0.000]
LM spatial error (classic)	70.82	16.69	23.96
	[0.000]	[0.000]	[0.000]
Robust LM spatial lag	0.1171	7.012	33.02
	[0.732]	[0.008]	[0.000]
Robust LM spatial error	24	0.7752	22.18
	[0.000]	[0.379]	[0.000]
Robust LM SAR	21.4	9.84	24.88
	[0.011]	[0.363]	[0.003]
Robust LM SEM	27.53	18.28	27.29
	[0.001]	[0.032]	[0.001]
LR tests for the joint		70.1	
Significance of spatial fixed effects		[0.000]	
LR tests for the joint		664.64	
Significance of time-period fixed effects		[0.000]	

Notes: This table provides the diagnostic tests for spatial dependence in panel model. The null hypothesis of LM spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of LM spatial lag test is that there is no spatially lagged dependent variable in the model. LR tests for the joint stands for the selection of fixed effect or time-period effect. P values are in square brackets.

Table A.149: Test Results for Spatial and Time-Period Fixed Effect Model with Spill-over Effects

	Spatial Durbin fixed effects model		
	Direct effect	Indirect effect	Total effect
Rho(ρ)	0.232**		
	(2.22)		
GDP	0.466***	0.365**	0.831***
	(5.24)	(2.49)	(4.93)
CPI	-2.470***	-0.713	-3.182
	(-2.65)	(-0.38)	(-1.55)
une_r	-0.499***	-0.565*	-1.064***
	(-4.06)	(-1.96)	(-3.06)
pop_den	-0.0498	-0.0854	-0.135
	(-1.50)	(-0.90)	(-1.29)
num_edu	0.0608	-0.665**	-0.604**
	(0.55)	(-2.30)	(-2.32)
num_heal	-0.174***	-0.0465	-0.221
	(-4.15)	(-0.25)	(-1.12)
num_lib	-0.226***	-0.0668	-0.293**
	(-3.52)	(-0.52)	(-1.99)
num_muse	-0.0312	0.0472	0.0161
	(-0.80)	(0.32)	(0.10)
size_building	-0.125**	0.0839	-0.0412
	(-2.04)	(0.49)	(-0.22)
Observation	496		
Log-likelihood	533.82		
Time fixed effect	Yes		
Wald test, spatial lag	24.88[0.003]		
Wald test, spatial	27.29[0.001]		
LR test, spatial lag	64.25[0.000]		
LR test, spatial	70.28[0.000]		

Notes: This table provides test results for spatial and time-period fixed effect model. The null hypothesis of LR spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of LR spatial lag test is that there is no spatially lagged dependent variable in the model. The null hypothesis of Wald test is that the model is homoscedastic.

Table A.150: Test Results for Predict House Prices Estimation with Spatial Fixed Effect

	Spatial fixed effect		
	Direct effect	Indirect effect	Total effect
Rho(ρ)	0.606***		
	(10.56)		
GDP	0.325***	0.408***	0.734***
	(12.86)	(11.08)	(16.58)
CPI	-1.043***	0.989***	-0.0538
	(-8.07)	(4.68)	(-0.32)
une_r	-0.135***	-0.561***	-0.696***
	(-4.57)	(-5.91)	(-5.88)
pop_den	-0.0171***	-0.00512	-0.0222
	(-4.65)	(-0.32)	(-1.37)
num_edu	0.00906	0.297***	0.306***
	(0.53)	(3.98)	(3.93)
num_heal	-0.0112***	0.123***	0.112***
	(-3.09)	(7.77)	(7.08)
num_lib	-0.0458***	-0.110***	-0.155***
	(-9.35)	(-3.40)	(-4.34)
num_muse	0.0149*	-0.249***	-0.234***
	(1.88)	(-4.10)	(-3.61)
size_building	-0.0401***	-0.267***	-0.307***
	(-3.73)	(-5.43)	(-6.00)
Observation	496		
Log-likelihood	1622.95		
Time fixed effect	No		
Wald test, spatial lag	24.88[0.003]		
Wald test, spatial	27.29[0.001]		
LR test, spatial lag	64.25[0.000]		
LR test, spatial	70.28[0.000]		

Notes: This table provides test results for spatial and time-period fixed effect model. The null hypothesis of LR spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of LR spatial lag test is that there is no spatially lagged dependent variable in the model. The null hypothesis of Wald test is that the model is homoscedastic.

Table A.151: Test Results for Predict House Prices Estimation with Time-period Fixed Effect

	Time-period fixed effect		
	Direct effect	Indirect effect	Total effect
Rho(ρ)	0.232		
	(1.74)		
GDP	0.480***	0.435***	0.916***
	(5.65)	(2.66)	(4.93)
CPI	-2.497***	-0.422	-2.919
	(-2.93)	(-0.24)	(-1.59)
une_r	-0.494***	-0.536*	-1.030***
	(-4.61)	(-1.84)	(-2.98)
pop_den	-0.0462*	-0.0423	-0.0885
	(-1.70)	(-0.57)	(-1.16)
num_edu	0.0500	-0.788***	-0.738***
	(0.45)	(-2.65)	(-2.72)
num_heal	-0.162***	0.0693	-0.0927
	(-3.82)	(0.42)	(-0.53)
num_lib	-0.237***	-0.120	-0.357**
	(-3.56)	(-0.97)	(-2.33)
num_muse	-0.0360	0.0270	-0.00901
	(-1.00)	(0.25)	(-0.07)
size_building	-0.124**	0.0747	-0.0497
	(-2.52)	(0.50)	(-0.30)
Observation	496		
Log-likelihood	615.46		
Time fixed effect	Yes		
Wald test, spatial lag	43.55[0.056]		
Wald test, spatial	69.87[0.065]		
LR test, spatial lag	52.19[0.071]		
LR test, spatial	31.52[0.083]		

Notes: This table provides test results for spatial and time-period fixed effect model. The null hypothesis of LR spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of LR spatial lag test is that there is no spatially lagged dependent variable in the model. The null hypothesis of Wald test is that the model is homoscedastic.

Table A.152: Test Results for Predict House Prices Estimation with Spatial and Time-period Fixed Effect

	Spatial and time-period fixed effect		
	Direct effect	Indirect effect	Total effect
Rho(ρ)	0.389***		
	(4.34)		
GDP	0.303***	0.222***	0.525***
	(10.96)	(2.81)	(5.81)
CPI	-1.008***	0.950***	-0.0583
	(-6.57)	(2.78)	(-0.15)
une_r	-0.137***	-0.457***	-0.595***
	(-5.74)	(-4.94)	(-5.32)
pop_den	-0.0238***	-0.0411**	-0.0649***
	(-7.00)	(-2.50)	(-3.80)
num_edu	0.0270	0.311***	0.338***
	(1.30)	(4.74)	(4.32)
num_heal	-0.0140***	0.0720***	0.0580***
	(-4.05)	(5.81)	(4.71)
num_lib	-0.0408***	-0.0583**	-0.0991***
	(-7.70)	(-2.06)	(-3.03)
num_muse	0.0250***	-0.157***	-0.132***
	(3.55)	(-3.69)	(-2.86)
size_building	-0.0411***	-0.219***	-0.260***
	(-4.17)	(-7.93)	(-9.55)
Observation	496		
Log-likelihood	1666.34		
Time fixed effect	Yes		
Wald test, spatial lag	27.63[0.011]		
Wald test, spatial	39.17[0.013]		
LR test, spatial lag	78.71[0.000]		
LR test, spatial	55.32[0.000]		

Notes: This table provides test results for spatial and time-period fixed effect model. The null hypothesis of LR spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of LR spatial lag test is that there is no spatially lagged dependent variable in the model. The null hypothesis of Wald test is that the model is homoscedastic.

Table A.153: Results of ARCH Family Regression

	Arch L1. Coef.	**Garch L1. Coef.**	**Constant Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
y2000	-0.2346	1.4877	-2.46E-04	9.12E-05	-2.7	0.007	-4.25E-04	-6.73E-05
y2001	-0.2134	1.4317	1.18E-04	1.16E-03	0.1	0.919	-2.16E-03	2.40E-03
y2002	-0.2377	1.4670	7.00E-04	7.06E-04	0.99	0.321	-6.84E-04	2.08E-03
y2003	0.1061	-1.4696	3.93E-02	4.66E-03	8.44	0	3.02E-02	4.84E-02
y2004	-0.2209	1.4625	-3.53E-04	1.48E-03	-0.24	0.812	-3.26E-03	2.55E-03
y2005	-0.2572	1.4928	2.35E-04	7.54E-05	3.11	0.002	8.69E-05	3.83E-04
y2006	-0.0995	0.2194	2.60E-02	7.07E-03	3.68	0	1.21E-02	3.98E-02
y2007	-0.1008	0.4733	1.90E-02	2.04E-02	0.93	0.352	-2.10E-02	5.89E-02
y2008	-0.1168	0.2944	2.73E-02	4.12E-02	0.66	0.507	-5.34E-02	1.08E-01
y2009	0.0805	-1.2628	4.88E-02	2.06E-02	2.37	0.018	8.41E-03	8.91E-02
y2010	-0.1217	0.0826	4.08E-02	6.54E-02	0.62	0.533	-8.74E-02	1.69E-01
y2011	-0.1367	0.4306	2.79E-02	3.00E-02	0.93	0.351	-3.08E-02	8.67E-02
y2012	-0.1500	0.4385	2.82E-02	3.52E-02	0.8	0.423	-4.08E-02	9.73E-02
y2013	-0.1212	0.4148	2.37E-02	1.58E-12	1.50E+10	0	2.37E-02	2.37E-02
y2014	0.1262	-1.4721	4.79E-02	3.77E-03	12.69	0	4.05E-02	5.53E-02
y2015	-0.1129	0.1314	3.21E-02	4.97E-02	0.65	0.518	-6.53E-02	1.30E-01

Notes: This table provides test results for ARCH family regression. yxxxx represents the house price in the year xxxx.

Table A.154: LM Test for Autoregressive Conditional Heteroskedasticity (ARCH)

	lags(p)	**chi2**	**df**	**Prob>chi2**
y2000	1	0.77	1	0.3802
y2001	1	0.657	1	0.4176
y2002	1	0.718	1	0.3969
y2003	1	0.774	1	0.379
y2004	1	0.637	1	0.4249
y2005	1	0.758	1	0.3839
y2006	1	0.888	1	0.346
y2007	1	0.832	1	0.3616
y2008	1	0.991	1	0.3195
y2009	1	1.088	1	0.2969
y2010	1	1.033	1	0.3096
y2011	1	1.17	1	0.2795
y2012	1	1.212	1	0.2709
y2013	1	1.222	1	0.269
y2014	1	1.11	1	0.2922
y2015	1	1.148	1	0.2841

Notes: This table provides LM test for autoregressive conditional heteroskedasticity. H0: no ARCH effects vs. H1: ARCH(p) disturbance.

Table A.155: House Prices Forecasting Parameter Estimates by Year

Year	Intercept		Lagged 1 year price			
	Parameter estimate	Standard errors	Parameter estimate	Standard errors	LM-test	p-value
2000	3.464	(0.021)	-0.0002	(0.0001)	0.770	0.00
2001	3.458	(0.021)	0.0001	(0.0012)	0.657	0.01
2002	3.463	(0.018)	0.0007	(0.0007)	0.718	0.00
2003	3.481	(0.021)	0.0393	(0.0047)	0.774	0.00
2004	3.461	(0.020)	-0.0004	(0.0015)	0.637	0.00
2005	3.464	(0.018)	0.0002	(0.0001)	0.758	0.02
2006	3.424	(0.049)	0.0260	(0.0071)	0.888	0.00
2007	3.409	(0.015)	0.0190	(0.0204)	0.832	0.00
2008	3.417	(0.040)	0.0273	(0.0412)	0.991	0.00
2009	3.394	(0.014)	0.0488	(0.0206)	1.088	0.00
2010	3.365	(0.017)	0.0408	(0.0654)	1.033	0.00
2011	3.352	(0.025)	0.0279	(0.0301)	1.170	0.00
2012	3.368	(0.052)	0.0282	(0.0352)	1.212	0.00
2013	3.364	(0.023)	0.0237	(0.0021)	1.222	0.01
2014	3.388	(0.029)	0.0479	(0.0038)	1.110	0.00
2015	3.371	(0.062)	0.0321	(0.0497)	1.148	0.00

Notes: This table summarises house prices forecasting parameter estimates by year.

Table A.156: The Effect of House Prices Uncertainty in Neighbouring Regions on Timing of Development and Land Prices

Explanatory variables	Timing of development		Land Prices
	Spatial		OLS
	landprice	Wx	landprice
fpriceh	2.984	1.428	0.576***
	(1.34)	(1.20)	(6.44)
uncer	-1.101***	0.176	1.829***
	(-3.78)	(0.27)	(5.21)
GDP	0.409	0.855	0.496***
	(-0.80)	(-0.90)	(16.10)
CPI	1.875	5.029*	1.601
	(-0.51)	(1.69)	(0.92)
une_r	-0.539**	-1.423**	-0.402***
	(2.06)	(1.98)	(-2.61)
pop_den	0.101	0.298	0.219***
	(1.44)	(1.40)	(4.48)
num_edu	-0.465	-1.574**	-
	(-1.42)	(-2.08)	
num_heal	-0.00546	0.360**	-
	(-0.09)	(2.00)	
num_lib	0.0264	-0.214	-
	(0.36)	(-0.63)	
num_muse	-0.264*	0.174	-
	(-1.87)	(0.51)	
size_building	0.0335	0.495	-
	(0.32)	(1.14)	
Observation	496		496
Log-likelihood	722.95		
Time fixed effect	Yes		Yes
Wald test, spatial lag	26.16[0.021]		
Wald test, spatial	29.82[0.016]		
LR test, spatial lag	58.37[0.000]		
LR test, spatial	64.58[0.000]		

Notes: This table provides test results for spatial and time-period fixed effect model. The null hypothesis of LR spatial error test is that there is no spatially lagged error term in the model. The null hypothesis of LR spatial lag test is that there is no spatially lagged dependent variable in the model. The null hypothesis of Wald test is that the model is homoscedastic.

Table A.157: Regressions of Market Prices on Model Prices

	Constant	Std.	Coeff.	Std.	R-square
	a	Error	b	Error	
2000	1.0577	0.0484	0.3901	0.0130	0.9679
2001	1.0457	0.0514	0.3888	0.0135	0.9653
2002	1.0827	0.0520	0.3784	0.0135	0.9634
2003	1.0074	0.0406	0.3970	0.0099	0.9816
2004	0.8819	0.0306	0.4045	0.0069	0.9914
2005	0.9938	0.0368	0.3927	0.0081	0.9873
2006	0.7548	0.0533	0.4431	0.0111	0.9814
2007	0.8016	0.0368	0.4308	0.0072	0.9917
2008	0.7537	0.0393	0.4343	0.0074	0.9915
2009	0.9648	0.0454	0.4071	0.0083	0.9876
2010	0.7696	0.0508	0.4315	0.0088	0.9876
2011	0.7623	0.0496	0.4307	0.0084	0.9886
2012	0.7718	0.0458	0.4300	0.0074	0.9912
2013	0.4302	0.0057	0.7546	0.0359	0.9948
2014	0.8770	0.0311	0.4166	0.0047	0.9962
2015	0.7893	0.0325	0.4291	0.0047	0.9964

Notes: This table provides regressions of maarket prices on model prices. The models are well specified if the coefficients are not significantly different from zero, and the constants are not significantly different from one. Option model: $land\ market\ price = a + b * option\ model\ price + \varepsilon$

Table A.158: Volatility of House Prices

Region	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Anhui	18.38%	18.85%	19.32%	13.75%	19.02%	19.16%	17.35%	18.04%	18.37%	13.77%	19.79%	20.07%	19.91%	18.77%	9.77%	18.12%
Beijing	22.12%	22.45%	23.49%	19.36%	22.83%	23.38%	18.04%	18.52%	19.29%	22.08%	20.96%	21.25%	21.35%	19.56%	21.86%	19.09%
Chongqing	8.01%	8.80%	7.49%	11.69%	9.13%	9.30%	5.03%	9.00%	4.97%	12.76%	4.75%	9.39%	17.30%	15.21%	12.37%	14.46%
Fujian	9.60%	10.50%	9.42%	13.88%	10.88%	11.46%	16.12%	13.77%	16.53%	16.80%	20.19%	16.71%	16.80%	15.38%	15.95%	17.93%
Gansu	9.92%	10.59%	9.56%	11.48%	10.71%	11.05%	16.68%	15.33%	17.25%	13.36%	19.10%	17.48%	17.70%	16.19%	12.76%	17.32%
Guangdong	11.54%	12.17%	11.43%	14.48%	12.51%	13.03%	17.77%	17.21%	18.73%	16.56%	20.68%	20.05%	20.21%	18.37%	15.91%	18.76%
Guangxi	7.78%	7.85%	6.00%	12.52%	7.32%	6.98%	15.06%	14.76%	15.96%	15.27%	17.28%	16.93%	17.45%	15.77%	14.50%	16.20%
Guizhou	9.32%	9.45%	7.72%	12.77%	8.63%	8.65%	17.59%	17.11%	18.66%	13.91%	20.79%	20.06%	20.39%	18.43%	13.06%	18.86%
Hainan	8.68%	9.58%	7.69%	13.02%	8.56%	8.97%	17.78%	17.80%	19.02%	15.89%	20.79%	20.95%	21.27%	19.17%	15.68%	18.91%
Hebei	5.69%	4.60%	3.01%	12.93%	5.63%	3.98%	16.77%	16.90%	17.97%	14.67%	19.10%	18.72%	19.04%	16.94%	14.08%	16.54%
Heilongjiang	6.76%	5.61%	4.48%	12.22%	6.25%	4.76%	17.93%	18.02%	19.18%	14.70%	20.92%	20.74%	20.99%	18.85%	13.74%	18.90%
Henan	7.56%	6.58%	5.82%	13.18%	7.04%	5.79%	18.17%	18.53%	19.52%	14.72%	21.03%	21.54%	21.74%	19.54%	14.28%	19.17%
Hubei	7.67%	6.74%	6.21%	12.23%	6.84%	5.93%	18.13%	18.64%	19.49%	14.77%	20.95%	21.73%	21.91%	19.70%	13.78%	19.09%
Hunan	9.19%	8.12%	7.97%	13.17%	8.06%	7.39%	18.19%	18.79%	19.60%	14.59%	21.03%	21.94%	22.16%	19.91%	14.12%	19.18%
Inner Mongolia	8.81%	8.28%	8.06%	12.46%	8.04%	7.62%	18.05%	18.69%	19.44%	15.01%	20.90%	21.85%	22.09%	19.77%	14.22%	18.97%
Jiangsu	9.60%	8.98%	8.14%	13.31%	8.14%	7.09%	17.60%	18.09%	18.64%	15.30%	19.75%	20.59%	21.18%	18.93%	14.48%	18.34%
Jiangxi	7.69%	7.59%	6.45%	12.54%	7.50%	6.80%	17.88%	18.40%	19.20%	14.00%	20.87%	21.40%	21.71%	19.48%	13.51%	18.95%
Jilin	9.24%	9.15%	8.20%	12.79%	8.76%	8.34%	18.14%	18.68%	19.51%	15.51%	21.06%	21.82%	22.09%	19.82%	14.55%	19.20%
Liaoning	9.65%	9.32%	9.13%	12.54%	9.62%	9.33%	17.93%	18.59%	19.28%	13.81%	20.73%	21.63%	21.98%	19.71%	13.30%	18.84%
Ningxia	9.18%	9.53%	9.27%	13.73%	10.15%	9.99%	17.92%	18.58%	19.24%	15.96%	20.88%	21.71%	21.88%	19.64%	15.29%	19.00%
Qinghai	10.59%	11.22%	11.35%	11.06%	11.96%	12.08%	18.09%	18.73%	19.30%	13.07%	20.99%	21.88%	22.10%	19.83%	11.88%	19.15%
Shaanxi	12.51%	13.15%	13.60%	14.84%	14.21%	14.42%	18.06%	18.73%	19.29%	16.88%	20.88%	21.86%	22.06%	19.84%	16.80%	19.09%
Shandong	15.10%	15.77%	16.67%	8.34%	17.07%	17.66%	18.19%	18.84%	19.56%	11.30%	21.05%	22.02%	22.26%	19.99%	17.98%	19.21%
Shanghai	18.34%	18.89%	20.34%	17.06%	20.54%	21.62%	18.16%	18.83%	19.59%	18.10%	21.02%	22.05%	22.31%	20.01%	19.64%	19.17%
Shanxi	8.87%	8.67%	7.51%	14.22%	8.42%	8.05%	7.79%	8.33%	8.09%	18.02%	7.26%	6.26%	4.82%	5.19%	16.04%	6.86%
Sichuan	10.10%	9.92%	9.07%	10.13%	9.61%	9.43%	16.47%	14.81%	16.97%	9.07%	20.18%	17.07%	16.98%	15.61%	10.42%	18.00%
Tianjin	12.20%	11.87%	11.21%	15.57%	11.46%	11.61%	17.87%	17.13%	18.91%	19.64%	21.00%	20.10%	20.20%	18.35%	17.93%	19.07%
Tibet	7.61%	8.53%	7.53%	9.35%	8.86%	8.64%	16.01%	15.79%	16.72%	8.92%	17.79%	17.62%	17.52%	15.79%	10.93%	15.59%
Xinjiang	9.13%	10.19%	9.46%	16.27%	10.55%	10.59%	17.77%	17.53%	18.65%	19.80%	20.79%	20.22%	19.99%	18.16%	17.68%	18.77%
Yunnan	10.88%	12.02%	11.62%	2.60%	12.56%	12.81%	17.97%	18.13%	19.21%	2.14%	20.81%	21.10%	21.06%	19.08%	5.74%	18.99%
Zhejiang	12.97%	14.22%	14.20%	19.59%	15.05%	15.71%	18.18%	18.57%	19.53%	21.96%	21.06%	21.70%	21.81%	19.65%	20.86%	19.17%

Table A.159: Statistics of Option Premium

Region	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Anhui	16.23%	18.10%	17.67%	18.73%	18.13%	17.73%	18.34%	15.00%	17.92%	17.18%	16.45%	16.69%	21.00%	12.71%	12.62%	13.85%
Beijing	16.89%	11.85%	17.58%	17.66%	18.76%	17.50%	19.03%	18.34%	15.32%	18.32%	17.13%	16.52%	19.78%	17.28%	12.42%	13.97%
Chongqing	17.34%	12.66%	12.51%	17.95%	16.57%	18.13%	18.77%	19.22%	17.74%	15.41%	18.19%	17.20%	16.56%	14.99%	17.14%	11.16%
Fujian	14.20%	12.61%	13.29%	11.77%	17.99%	16.94%	19.24%	18.96%	18.59%	18.36%	15.61%	18.22%	17.25%	15.78%	14.79%	18.04%
Gansu	20.37%	13.32%	13.22%	12.38%	12.06%	16.97%	17.02%	19.40%	18.50%	19.16%	18.27%	16.04%	18.35%	15.44%	15.57%	16.08%
Guangdong	18.67%	17.19%	13.24%	12.29%	12.93%	11.49%	18.13%	16.96%	18.97%	18.93%	19.11%	18.28%	16.60%	17.18%	15.87%	16.47%
Guangxi	16.19%	14.96%	17.53%	13.67%	12.66%	11.88%	11.74%	18.14%	17.10%	19.36%	18.83%	19.18%	18.34%	12.83%	17.08%	16.93%
Guizhou	16.88%	11.80%	15.48%	16.92%	13.88%	12.11%	12.09%	12.11%	17.76%	17.12%	19.28%	18.92%	19.27%	17.94%	12.78%	18.18%
Hainan	17.80%	13.21%	15.88%	14.47%	17.09%	13.54%	12.33%	12.50%	11.75%	18.15%	17.41%	19.37%	19.04%	17.00%	16.84%	11.79%
Hebei	14.65%	13.49%	15.67%	15.15%	14.87%	16.83%	13.55%	12.76%	12.31%	12.41%	18.05%	18.02%	19.44%	16.56%	17.24%	18.24%
Heilongjiang	17.76%	14.22%	17.31%	15.42%	16.39%	14.25%	16.88%	13.64%	12.37%	12.84%	12.77%	18.10%	19.23%	17.59%	16.80%	18.82%
Henan	18.35%	12.43%	14.48%	16.75%	16.78%	16.45%	14.33%	17.01%	13.68%	13.08%	13.53%	14.70%	18.13%	15.71%	17.66%	18.44%
Hubei	17.91%	14.02%	17.44%	15.30%	18.09%	16.88%	16.55%	14.58%	16.94%	13.68%	13.87%	15.46%	12.13%	17.61%	15.86%	19.04%
Hunan	18.91%	16.70%	17.17%	16.60%	15.58%	18.16%	17.16%	16.51%	14.44%	17.28%	13.07%	16.12%	12.62%	13.42%	16.56%	14.82%
Inner Mongolia	19.29%	17.43%	16.88%	16.93%	18.23%	15.05%	18.30%	17.18%	16.43%	14.97%	17.86%	12.08%	12.61%	13.79%	12.22%	18.05%
Jiangsu	17.66%	16.33%	17.82%	16.77%	18.75%	18.29%	15.08%	18.28%	17.05%	16.46%	15.82%	19.60%	14.41%	13.82%	13.14%	13.75%
Jiangxi	18.05%	16.10%	16.47%	17.66%	18.54%	18.66%	18.30%	15.19%	18.17%	17.14%	16.53%	18.03%	17.07%	15.02%	13.19%	14.78%
Jilin	18.61%	12.39%	17.31%	17.10%	19.08%	18.41%	19.12%	18.28%	14.75%	18.21%	17.21%	16.58%	14.66%	17.73%	15.34%	15.03%
Liaoning	19.34%	13.26%	13.15%	16.82%	17.57%	18.94%	18.85%	19.18%	18.27%	14.67%	18.22%	17.26%	12.36%	15.66%	17.49%	16.91%
Ningxia	16.80%	13.17%	13.91%	12.29%	18.02%	16.82%	19.31%	18.93%	18.97%	18.20%	14.35%	18.34%	13.01%	16.43%	15.33%	18.86%
Qinghai	21.97%	14.26%	13.90%	12.88%	11.26%	18.01%	16.83%	19.34%	18.75%	19.07%	18.33%	13.64%	13.97%	16.47%	16.38%	17.20%
Shaanxi	20.59%	17.57%	14.52%	12.67%	11.76%	11.71%	18.10%	17.00%	19.21%	18.88%	19.19%	18.35%	16.56%	18.04%	16.65%	16.57%
Shandong	16.51%	15.61%	18.02%	13.78%	12.07%	12.06%	12.24%	18.04%	16.73%	19.31%	18.94%	19.26%	12.83%	17.32%	17.93%	17.13%
Shanghai	17.11%	15.62%	16.16%	17.10%	13.85%	12.26%	12.45%	12.39%	18.03%	16.66%	19.36%	19.01%	13.29%	18.33%	17.40%	18.32%
Shanxi	18.21%	15.00%	16.38%	14.80%	16.80%	13.95%	12.73%	12.72%	12.26%	17.98%	16.16%	19.44%	12.57%	18.36%	18.23%	18.43%
Sichuan	18.49%	16.99%	16.50%	16.30%	14.23%	16.89%	13.95%	12.78%	12.78%	12.24%	18.13%	18.51%	14.85%	18.04%	18.42%	18.36%
Tianjin	18.31%	16.00%	17.96%	16.46%	15.92%	14.32%	17.01%	14.01%	12.80%	12.91%	13.56%	18.15%	17.71%	18.73%	17.94%	19.10%
Tibet	18.90%	17.95%	15.89%	17.93%	16.37%	16.57%	14.53%	17.03%	13.78%	13.13%	14.32%	16.22%	13.67%	18.50%	18.64%	18.80%
Xinjiang	18.58%	16.84%	18.18%	14.71%	17.62%	17.11%	16.58%	14.48%	17.12%	14.19%	14.77%	16.91%	12.58%	18.09%	18.39%	19.29%
Yunnan	19.25%	16.48%	18.34%	18.23%	15.04%	18.32%	17.23%	16.30%	14.72%	17.40%	14.69%	17.83%	13.05%	11.72%	17.95%	19.77%
Zhejiang	20.22%	17.50%	18.04%	18.35%	17.44%	15.06%	18.35%	16.91%	16.55%	15.15%	18.57%	15.71%	13.06%	12.58%	12.88%	18.13%

Appendix B

Figure B.1: Measures of Local Spatial Autocorrelation for the House Prices (**Chapter 5 The Spatial Analysis and Spill-over Effects of House Price in Beijing**)

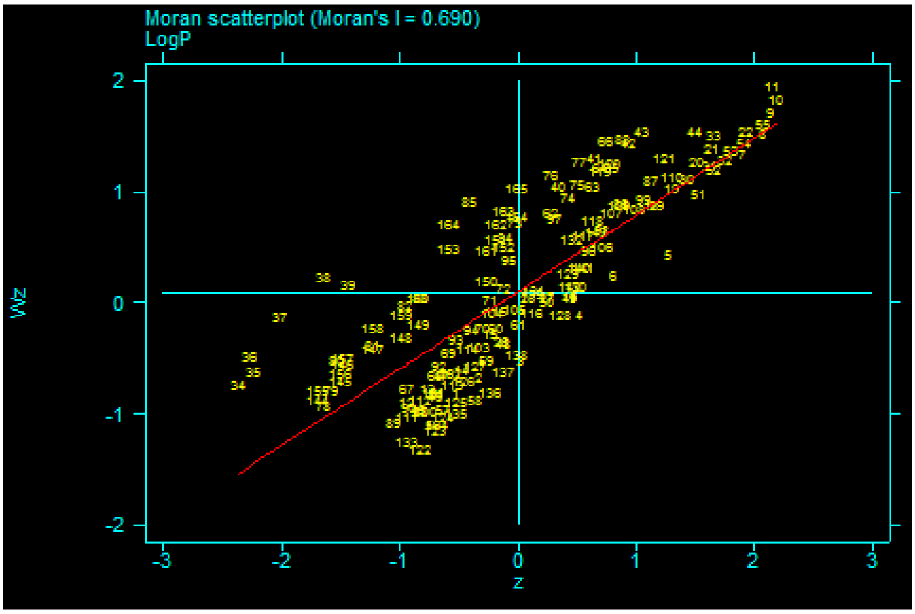


Figure B.2: Measures of Local Spatial Autocorrelation for House Prices of the Previous Year (**Chapter 5 The Spatial Analysis and Spill-over Effects of House Price in Beijing**)

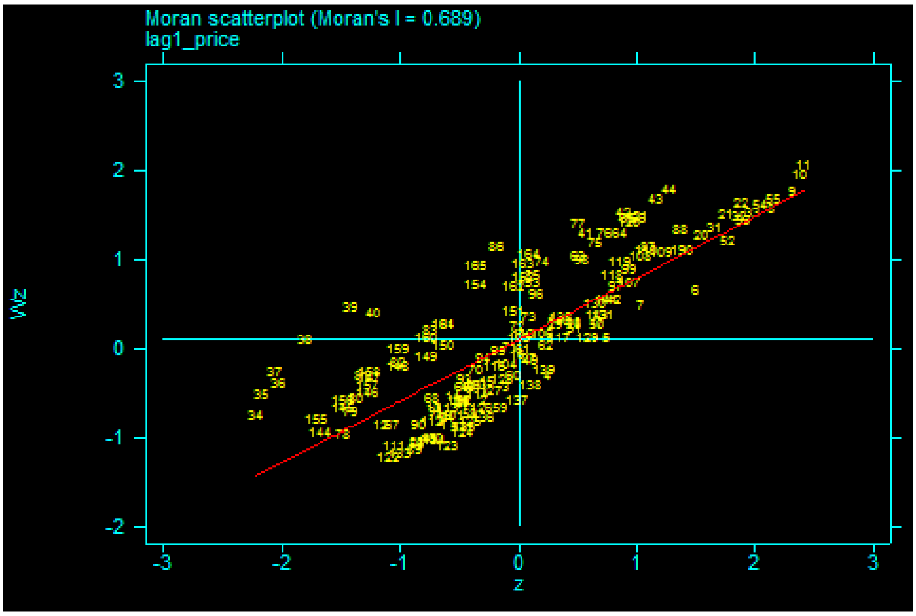
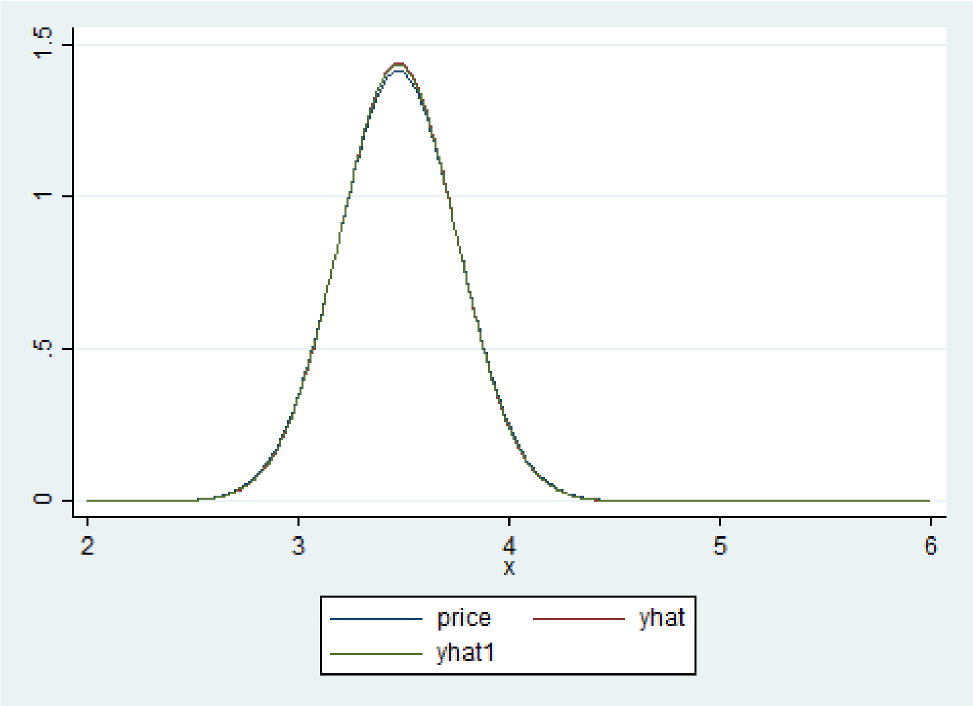


Figure B.3: Comparison between House Prices and Predict House Prices (**Chapter 6 The Uncertainty of House Prices and Real Options in China**)



Notes: This figure provides test results for comparison between house prices and predict house prices. price is the real house prices. yhat is the predict house prices with reduced-form mean. Yhat1 is the predict house prices the naive-form prediction.

FORM UPR16

Research Ethics Review Checklist

University of Portsmouth

Please include this completed form as an appendix to your thesis (see the Postgraduate Research Student Handbook for more information

Postgraduate Research Student (PGRS) Information			**Student ID:**	472292
PGRS Name:	Hui Zhi			
Department:	Economics and Finance	**First Supervisor:**	Dr Konstantinos Vergos	
Start Date: (or progression date for Prof Doc students)		**01/02/2014**		
Study Mode and Route:	Part-time ☐ Full-time ☒	MPhil ☐ PhD ☒	MD ☐ Professional Doctorate ☐	

Title of Thesis:	An enquiry into the Chinese housing market; evidence from spatial analysis and real options
Thesis Word Count: (excluding ancillary data)	85,808

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Although the Ethics Committee may have given your study a favourable opinion, the final responsibility for the ethical conduct of this work lies with the researcher(s).

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a) Have all of your research and findings been reported accurately, honestly and within a reasonable time frame?	YES ☒ NO ☐
b) Have all contributions to knowledge been acknowledged?	YES ☒ NO ☐
c) Have you complied with all agreements relating to intellectual property, publication and authorship?	YES ☒ NO ☐
d) Has your research data been retained in a secure and accessible form and will it remain so for the required duration?	YES ☒ NO ☐
e) Does your research comply with all legal, ethical, and contractual requirements?	YES ☒ NO ☐

Candidate Statement:

I have considered the ethical dimensions of the above named research project, and have successfully obtained the necessary ethical approval(s)

Ethical review number(s) from Faculty Ethics Committee (or from NRES/SCREC):	

If you have *not* submitted your work for ethical review, and/or you have answered 'No' to one or more of questions a) to e), please explain below why this is so:

This study do not require ethical approval include those involving information freely available in the public domain and the analysis of datasets, either open source or obtained from other researchers.

Signed *(PGRS)*:	智汇	**Date:** 10/06/2019