Urban Growth, Resident Welfare, and Housing Markets: Evidence from China

Yuanyuan Cai

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Urban Growth, Resident Welfare, and Housing Markets: Evidence from China

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Yuanyuan Cai

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Promotor:

Prof. dr. C. Castaldi

Copromotor:

Dr. M.J. Smit

Beoordelingscommissie:

Prof. dr. E. Buitelaar

Prof. dr. D. Ballas

Prof. dr. ir. ES van Leeuwen

Prof. dr. K. Frenken

Prof. dr. P. Hooimeijer

"Cities are structures; Cities are people". – Ed Glaeser (2011b, p. 9)

"Better city, Better life". – Overarching theme of the World Cities Day (*UN-Habitat, 2014*)

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Chapter 1 Introduction

1.1 Urban growth and residents' welfare

Cities have become the principal platform of economic growth. Around the world, they gather the majority of economic and industrial activities, and have grown significantly over the past decades. The importance of urban growth in residents' quality of life is becoming more and more evident, because of the intimate interaction between urban characteristics and human activities in urban settings (Bettencourt, 2013; Glaeser et al., 2001).

Cities shape urban residents' welfare, as cities provide amenities that improve or decrease their quality of life (Leyden et al., 2011). On one hand, urban contexts offer diversified opportunities and services (Kyttä et al., 2016): opportunities relate to higher wages and more specialized jobs (Redman & Jones, 2005), while services relate both to high-quality public services and to a range of consumer amenities that raise the living standard of urban residents (D'Ambrosio et al., 2020; Revi & Rosenzweig, 2013). On the other hand, urban growth also poses threats to urban resident welfare; both through high costs of living and through negative externalities. These include traffic congestion, environmental pollution, and even public health (Glaeser, 2011a), as the Covid-19 pandemic has shown (Jasiński, 2022). Overall, cities bring both benefits and disadvantages to their inhabitants.

At the same time, cities are complex and dynamic: they grow both with government planning and in more spontaneous ways (Bettencourt, 2021). Because of the complex way in which urban growth and residents' activities interact, it is increasingly difficult to figure out which kinds of urban features are positively or instead negatively associated with residents' quality of life. This puzzle makes it harder to clarify whether cities can provide enough net welfare to their residents. In fact, balancing the positive and negative implications of urban growth is on top of the agendas of urban planners and managers, with resident welfare as a key policy goal (Mulligan et al., 2004). Thus, a major challenge is to understand and evaluate how and to what extent urban growth shapes the welfare of urban residents.

The link between cities and welfare has been hotly debated in urban geography, economic geography, urban economics, and other related disciplines, yet we still have a limited grasp of how urban growth may impact residents' welfare, both theoretically and empirically. Two particular problems stand out that aggravate this situation. First, insights on the relationship between urban growth and residents' welfare in developed countries may not be appropriate for developing or emerging countries, because of the specific features of their urbanization and development processes (Haneef et al., 2021). Urbanization in rapidly emerging and developing countries, especially in Asia, has been found to follow less orderly and more rapid processes than urbanization in developed economies of the Global North (Randolph & Storper, 2022; Tian et al., 2022). As such, the processes in emerging economies may expose the paradoxes of urban growth for residents' welfare in a more striking way.

Second, current research is struggling to take into account the complexity of the relationship between urban growth and resident welfare. In particular, many recognize that the scope of urban welfare for residents is growing from an economic focus to one that also acknowledges social and environmental issues, with a key role for policy too. Moreover, spatial inequalities are becoming more and more important in research in urban and economic geography – some even say this line of research is becoming a pivotal branch (Nijman & Wei, 2020). Yet, most studies concentrate only on a specific geographical scale, and they ignore the distribution of welfare within the regions researched. Finally, by focusing on one dimension of urban welfare at a time, most studies ignore that the interaction between urban growth and resident welfare may touch upon multiple dimensions of welfare at the same time.

1.2 Urban growth in China

This thesis focuses on urban growth in China. Currently, China's urban system consists of 685 administrative areas called cities (National Bureau of Statistic of China, 2021), each of which is at a different stage of economic growth and has distinct urban spatial features. Chinese cities have shown rather specific trajectories of urban growth, against the background of a newly industrializing and developing country. There are several reasons why a focus on Chinese cities is particularly relevant for understanding the relation between urban growth and resident welfare.

First, with speedy urbanization and industrialization, the uniquely compressed development in a short period brings significant economic growth in China but at the same time problematic environmental pollution (Henderson et al., 2009). Since the economic reform and opening-up that started in 1978, China has experienced an average growth rate of real GDP per capita annually of 9.2%, and the urbanization ratio went from 17.5% to 63.9% (World Bank, 2022). At the same time, residents of Chinese cities have also significantly been confronted with hazardous levels of water and air pollutants. The territorial carbon dioxide (CO_2) emissions from fossil fuel combustion and industrial processes in China have been constantly rising, reaching 11.47 billion metric tons in 2021 from 1.49 billion tons in 1979 (Global Carbon Budget, 1979-2021). A lack of environmental quality has become one of the biggest threats to residents' physical and mental health in China, especially in urban areas (Kuerban et al., 2020).

Second, urban amenities and services in Chinese cities can be chaotic and inefficiently planned, given this background of rapid urbanization, which has led to a high density and strong mixing of residential and commercial uses. Those kinds of spatial patterns and provision of services can make it even more problematic for residents to meet their daily needs. Such as, the differentiated allocation of public services segregates urban welfare across social groups (Wu

& Li, 2005). Also, traffic congestion and other dis-amenities increasingly appear as the inefficient planning and management of urban facilities combines with an overgrowing population in cities (Normile, 2016). Scholars have questioned how the spatial layout of urban amenities in Chinese cities is affecting residents' lives (Li et al., 2019).

Third, the Chinese context is characterized by strong policy interventions. Specifically, transformational regional integration policies have been developed to promote regional development and cooperation, by imitating integration policies in the European Union and the United States (Mattli, 1999). Examples of such policies include metropolitan zones, and political institutions at the level of major urban agglomerations like the Yangtze River Delta Urban Agglomeration and the Pearl River Delta Urban Agglomeration (Fang & Yu, 2017), and these policies again affect resident welfare (Gong et al., 2015).

Finally, urban housing markets in China have undergone major transformations. A work-related social housing system[1] was standard in the period 1949-1978. Afterwards, a series of market-oriented reforms for urban housing started in 1988, allowing houses to be sold on markets. This prompted financialization of housing markets, as housing quickly became a private commodity to trade and invest (Ya & Murie, 1996). The reforms also helped to accelerate migration into cities, by increasing urban housing supply and activating urban real estate markets in China. Since then, the privatized housing markets have increasingly become crucial in urban development for residents' social welfare in China including affordable housing and its adequate supply (Yao et al., 2014). The property market, accounting for 29% of GDP in 2021 (Rogoff & Yang, 2021), has become a "pillar" of China's economy, but suffers from overheated speculation (Glaeser et al., 2017). Thus, it influences residents' economic welfare and has become a key regional economic indicator.

1.3 This thesis's research question

As discussed above, China is a typical example of very rapid urbanization and development processes. This thesis' central claim is that housing market dynamics can be studied to understand the tensions between the positive and the negative effects of urban growth on resident welfare. That leads to the following research question:

> *What do housing market dynamics reveal about the relationship between urban growth and resident welfare in China?*

Housing markets are closely intertwined with urban growth and residents' daily lives. Hence, they offer a way of evaluating several aspects of urban resident welfare (Doling & Ronald,

[1] The Bureau of Housing Management in the national government allocated housing to employees as welfare, but workers only had the right to live in the houses while the ownership of the houses belonged to the work unit or the state (Ya & Murie, 1996).

2010). Prior studies have exploited housing market dynamics and resident welfare, also in China. This thesis aims at expanding current insights by taking seriously two key issues.

Firstly, the thesis acknowledges the multi-dimensional nature of urban resident welfare. In particular, the focus is on integrating social, environmental, policy, and economic considerations. This effort is both conceptual and empirical. Conceptually, I analyse the different dimensions by focusing on specific tensions (for instance how wet markets combine social amenities and environmental dis-amenities in Beijing). Methodologically, I capture welfare with original data and advanced techniques. What's more, considering the social and spatial intertwining in most cases, spatial inequality of urban growth plays a crucial role in residents' quality of life (Buitelaar et al., 2017).

Secondly, I take a multi-scalar approach by showing that different scales show different processes at play. In detail, the analyses are at intra-city, inter-city, and regional levels, which is useful in order to figure out and compare the weights of the welfare impacts of urban features and their influence pathways across scales. As such, I contribute to research across all scales and can offer more precise suggestions to optimize urban welfare.

Overall, the thesis offers an original analysis and innovative empirical evidence on the relationship between urban growth and urban residents' welfare, with relevance for scholars and policymakers alike.

1.4 Research approach

1.4.1 Measurement strategy: Housing and resident welfare

In this thesis, housing market dynamics are leveraged to investigate the relationship between urban growth and resident welfare.

Housing is critical to residents' welfare, in many ways. Firstly, housing, as a fundamental social service, meets basic shelter needs (Goodman & Kawai, 1982). Secondly, housing has become the most important asset of households as well as their most important source of debt (Ronald & Dewilde, 2017). Thirdly, housing prices reflect the welfare of urban amenities, whether built or natural. According to Rosen (1974)'s framework, the location choice of residential housing is a trade-off between the appeal of neighborhood facilities and housing prices. Beyond the pure construction costs of housing, the total transaction price of housing also covers the shadow value of urban facilities contributing to occupants' welfare (Diamond & Tolley, 2013). Finally, housing prices are also one of the most widely available economic indicators, representing regional price indicators generally. Given their correlation with the economic cycle and given that housing costs account for the major part of the cost of living (Girouard & Blöndal, 2001), regional housing price dynamics can be seen as a barometer to track regional development, and as an indicator to monitor the efficiency of related policies.

1.4.2 Theoretical approaches

1.4.2.1 Hedonic prices theory for cost-benefit analysis

Cost-benefit analysis is commonly applied in the field of urban and regional development projects to evaluate economic and wider societal effects in welfare economics (Bronsteen et al., 2012). It can be employed towards two broad objectives: economic efficiency in the use of the resources available to society (or its dynamic equivalent, economic growth), and equity in the distribution of welfare between different groups (e.g., income classes, regions, generations) (Schofield, 1987). In Chapters 2-4, the results could be seen or used as a cost-benefit analysis to evaluate the welfare effect of urban characteristics by calibrating their costs or benefits non-monetarily and monetarily. Hedonic price analysis serves to monetize the non-financial effects of urban development (Scotchmer, 1985).

Under the hedonic price framework (Rosen, 1974), housing is a typical example of what is termed a differentiated good in the economics literature. Such goods consist of a diversity of features that, while differing in a variety of characteristics, are so closely related in consumers' minds that they are considered as one commodity. Market forces determine that different varieties of the product command different prices and that these prices depend on the individual products' exact characteristics. The price paid for housing in the housing market is determined by the particular qualities or quantities of surrounding urban features, in addition to the structure itself.

Consequently, in a static equilibrium assumption, not considering labor flows across space, we can weigh how important urban features in cities are for residents' welfare, based on the willingness to pay (WTP) of individuals/households for urban features they prefer (Freeman III, 1974). I will briefly go through the main theoretical features of such a model.

Housing, as a tradable commodity, can be described by a bundle of n attributes or characteristics, gathered in a vector $h = (h_1, h_2, \dots, h_n)$, which represents set containing the housing structure itself, its accessibility, characteristics of the neighborhood, and environmental features.

On the consumer's side of the hedonic price function, each housing has a quoted market price and is also associated with a fixed value of the vector h, so that housing markets implicitly reveal a function $p(h) = p(h_1, h_2, \dots, h_n)$ relating prices and characteristics. These prices reflect the consumer's valuation of any package of related characteristics. The total utility is a function of housing characteristics, h, and a composite commodity, x, whose price is set to unity. For each individual or household, the maximized utility is subject to the available budget and existing set of prices, represented in Eq. (1), where y is income:

$$({}_{h}, x^{Max} U\left(x, p(h_1, h_2, \ldots, h_n)\right) \text{ subject to } y = p(h) + x \qquad (1)$$

Therefore, based on the first-order condition, the marginal implicit price of a contained characteristic h_n is given in Eq. (2):

$$\frac{\partial p(h)}{\partial h_n} = \frac{U_{h_n}}{U_x} = p(h_n) \qquad (2)$$

referring to the increase in expenditure on a housing unit to obtain a housing unit with one unit of h_n, $\frac{\partial p(h)}{\partial h_n}$ can denote the implicit price of the h_n. When in equilibrium, the marginal implicit price of h_n equals the corresponding marginal WTP for an increase in the specific characteristic. This shows that the housing price gradient reveals the marginal value of urban features to residents. The hedonic price theory can then be adopted to evaluate policies, urban amenities, environmental externalities, and other urban features related to housing choice.

1.4.2.2 Regional convergence

Regional disparity is one of the key aspects affecting residents' welfare, and regional convergence is one of the theoretical approaches to capture the process of regional distribution dynamics. Regional convergence have been studied based on different growth theories, generally uncovering spatial unevenness by means of economic indicators such as income and GDP per capita (Barro & Sala-i-Martin, 1992; Rey & Janikas, 2005). To date, several forms of convergence including stochastic convergence, absolute convergence, σ- and β-convergence have been applied in prior research (Magrini, 2004), all of which test whether regions would tend toward a single equilibrium but with different evolutional paths. However, scholars question whether it is possible for all regions to converge into a common steady state, given that the structural characteristics of regions vary and develop heterogeneously over time (Bartkowska & Riedl, 2012; Tsai, 2018). The four types of convergence analysis referred to above all assume convergence to one equilibrium for all observations. Instead, club convergence allows for a wider heterogeneity across individual observations as well as over time (Phillips & Sul, 2007). It enables the identification of regional groups with similar price growth paths, and individual growth trajectories of each club.

To measure spatial inequalities, researchers often use basic economic indicators such as income and employment levels. However, housing prices can also be used to measure spatial inequalities (Penm & Terrell, 1994). The dynamic behavior of housing prices across regions reflects regional differences in the cost of living and more generally in economic prosperity, which is closely correlated with residents' welfare. Given regional housing market segmentation, it is quite possible multiple equilibria (i.e., club convergence) is present in housing markets between different cities. Hence, in the second part of this thesis, we apply the concept of club convergence to regional inequalities in China.

1.5 A multi-dimensional perspective on residents' urban welfare

As discussed above, the relationship between urban growth and resident welfare is a complex one (Ballas, 2013; Cardoso et al., 2021). The multidimensional nature of resident welfare means that urban growth might have a differential impact on the underlying dimensions, including the economic, social, environmental and policy ones. This thesis illustrates in selected cases how the different dimensions play a role.

Economic dimension. The economic components of cities offer the underlying economic support for residents' material living, which is closely tied to citizens' quality of life. Aside from the typical indicators of income, employment, and wealth (Clark et al., 2008; D'Ambrosio et al., 2020; Easterlin, 2001), housing should not be overlooked; it is a vital item of wealth to trade and invest in, as well as one of the major burdens for the cost of living in a city. Hence, housing prices are one of the key economic indicators at the regional level, alongside GDP and income. They allow for a representative proxy for regional price levels (Suedekum, 2006). The regional distribution of housing prices then reflects the disparities in inhabitants' economic welfare. Throughout this thesis, regional housing prices are a key economic dimension. In particular, evidence of the spatial distribution of welfare across regions is presented in Chapter 5.

Social dimension. The social dimension of urban welfare considered in this thesis relates to urban amenities. Urban amenities are understood as the non-residential facilities in a neighborhood that are linked to the daily life needs of residents (Kelly, 2006). The social dimension of urban resident welfare thus refers to the different types of urban amenities that satisfy the diverse welfare needs of residents. Public amenities such as public transportation, schools, and hospitals provide the basic needs of living in cities for commuting, education, healthcare, and entertainment. Moreover, consumption and cultural amenities such as recreational facilities, restaurants, and museums, are also beneficial to residents' happiness, providing venues for health-promoting activities, informal meeting places. They allow for social interaction and provide spaces to form and maintain in-person social networks (Allen, 2016). In Chapter 2, we study wet markets as public amenities with a social function for residents, and the social welfare is considered in Chapters 4 and 5 as well.

Environmental dimension. Environmental factors encompass climate, precipitation, pollution, and other natural factors, which have an evident influence on residents' physical and mental health, and well-being (Bosch, 2017). Environmental factors including landscape or greenspace have a positive influence on living health – through improving daily activities and lessening mental pressure (Laffan, 2018). Poor environmental quality has instead an inverse effect on residents' welfare (Chasco & Gallo, 2013; Li & Managi, 2022). Increasing pressure from population growth and the need for economic development threatens the benefits provided by the environment. In this thesis, Chapter 3 focuses on air quality and its dynamic welfare effect.

Policy dimension. Urban planning policies are government measures taken to manage urban development and quality of life (Grover & Singh, 2020; Pfeiffer & Cloutier, 2016). Some plans are directly targeted to boost residents' well-being – for instance, a series of environmental protection policies in China (Song et al., 2019; Zheng & Kahn, 2017). On the other hand, some urban policies like planning new towns or urban regeneration projects will set parameters for residents' welfare indirectly, by creating more job opportunities and supplying or updating infrastructure and public amenities, etc. (Wen and Tao 2015; Baumont 2007). Thus, it can be seen that the role of governmental strategies in the improvement of residents' quality of life is important. Furthermore, apart from urban policies within cities, some planning policies between cities may have a positive external effect on residents' welfare in any of the participant cities (Xiao, 2005). Hence, we pay attention to the welfare effect of regional integration policy (i.e., city integration between two cities) in Chapter 4.

It is worth noting that the complexity of the interaction between urban growth and residents' activities determines that urban welfare from a certain urban feature cannot be explained from any single dimension exclusively, as there will always be overlap in different dimensions (Kamp et al., 2003). This thesis provides empirical evidence to underline that point.

1.6 Outline of the thesis

The thesis explores the relationship between urban growth and residents' welfare from multiple dimensions and scales from a spatial inequality perspective, by means of the housing market. The empirical cases capture urban welfare for residents comprehensively from the economic, social, environmental, and political facets. The spatial scales of the different studies extend from intra-city (the metropolis of Beijing) to inter-city (core-periphery integration between Kaifeng and Zhengzhou) and even countrywide scales (70 major cities of China).

This thesis consists of six chapters, for which Figure 1.1 provides an overview. Chapters 2 to 5 are based on papers that have been published in or submitted to peer-reviewed journals (Table 1.1). The structure of this thesis is as follows.

At the intra-city level, taking Beijing as the study area, Chapter 2 explores the (dis)amenity effect of an urban public service-wet market for urban residents, while Chapter 3 evaluates the change in residents' willingness to pay for air quality, employing fixed-effected regression with instrumental variables (IV).

At the inter-city level, under the background of regional integration, Chapter 4 analyzes the influences of regional integration policy on residents' lives in Kaifeng city of China.

At the regional level, Chapter 5 studies the dynamic convergence behavior of regional housing prices in 70 major cities of China, and further gauges its potential drivers. The thesis ends with a conclusion, where we return to the research question and elaborate on the theoretical and policy implications of this research. Section 1.5 below discusses the chapters in more detail.

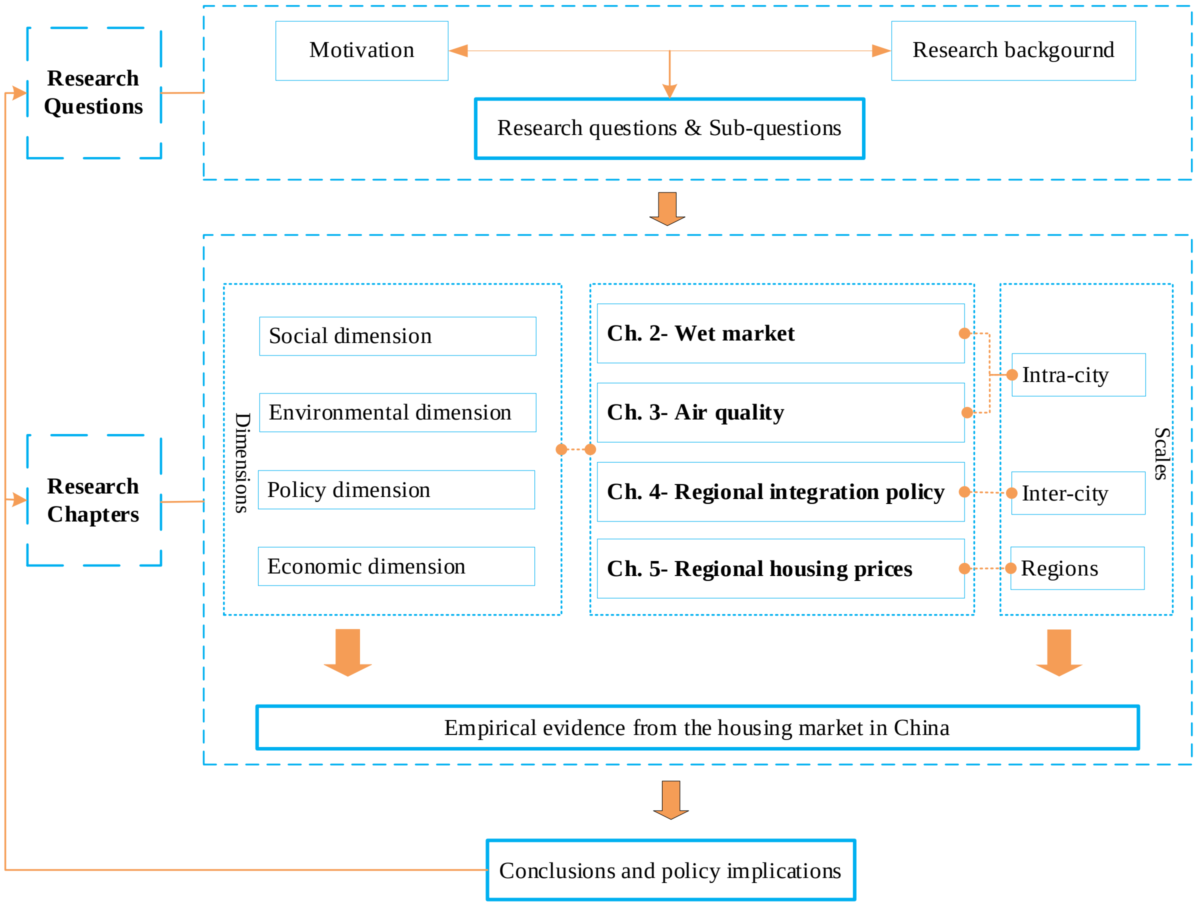

Figure 1.1 Thesis overview

1.7 Data and methodologies

Apart from public statistical data, web-scraping of big data allows us to construct new datasets. Both types of data can be geocoded using Geographical Information System (GIS) techniques to render geospatial datasets.

Big data used in the thesis is publicly available data scraped from websites. In particular the thesis exploits transaction data of housing from the websites of real estate brokers (Homelink, bj.lianjia.com/), used in Chapters 2-4, and information on points of interest (POIs) in cities including parks and schools, etc., extracted from Amap (amap.com/). Moreover, we scraped reviews (in this case, Dazhong Dianping, dianping.com/) and used them in Chapter 2, and we obtained air quality data from the Beijing Municipal Environmental Monitoring Center (http://www.bjmemc.com.cn/) for Chapter 3.

On the other hand, public statistical data on social and economic conditions and activities at city and regional levels is mainly used in Chapter 5, and was derived from different kinds of Statistical Yearbooks of China, such as the China City Statistical Yearbook (https://www.chinayearbooks.com/tags/china-city-statistical-yearbook).

The main methodological approaches are quantitative. Various econometric regression models are applied, including linear regression with and without spatial effects, as well as discrete regression. These serve various purposes. For instance, spatial econometric regressions efficiently address spatial issues such as spatial dependence, autocorrelation, and heterogeneity, and may not only lessen the estimated bias but also show the size of spatial spillover effects between neighboring regions (Chapters 2 & 4). Panel regression models capture the dynamic effects over time and allow us to handle endogeneity issues with instrumental variables (Chapter 3). Regarding research on policy, Chapter 4 adopts a spatial differences-in-differences analysis for cross-sectional data. Finally, Chapter 2 relies on quantile regressions to investigate heterogenous effects across income groups, while Chapter 5 exploits discrete regression Models.

1.8 Research chapters

Chapter 2.

Chapter 2 explores the welfare effect of urban amenities at the **social and environmental dimensions**, and at the **intra-city level**. Within cities, urban amenities are gradually being improved with urban development. Urban public infrastructure offers basic and convenient services for residents' life needs. Wet markets, recently thrust into the limelight during the coronavirus pandemic, play a necessary role in daily life in Asia. Despite their importance, the value of wet markets has not been explored yet. While an increasing body of work has studied the implicit value of urban public amenities through the hedonic price model and traditional measurements of accessibility and density, the subjective perceptions of (dis)amenities have been neglected, specifically for consumption amenities. This is especially the case with wet markets: traditional approaches are unable to capture their comprehensive effects.

Using cross-sectional data from Beijing, China, this second chapter of the thesis explores the following research questions:

How do urban amenities – wet markets with amenity and dis-amenity features- influence residents' welfare through housing prices?

To what extent are there differences in these influences between high- and low-income residents?

By employing data on Beijing housing transactions in 2019 and online review scores of wet markets, we reduce this knowledge gap by exploring both the amenity and dis-amenity effects of wet markets and capturing objective and subjective perspectives. Our results indicate a nonlinear relationship between wet market accessibility and urban housing prices. Considering the perceived quality of wet markets, this paper further indicates that housing prices near high-scoring wet markets appreciate while housing prices depreciate near low-scoring markets. Interestingly, the negative influence of low-scoring markets is statistically larger than the positive influence of high-scoring wet markets. Taking the housing price as a reflection of an owner's wealth and income level, we argue that high-income dwellers tend to pay more for perceived quality than for convenience.

Chapter 3.

Chapter 3 investigates the welfare effect of the natural environment; in other words, it studies the **environmental dimension,** and it does so at the **intra-city level**. In particular, it tackles negative externalities that come with rapid urbanization processes. Air pollution is a major environmental urban issue, particularly in fast-growing cities in developing countries. Reducing air pollution is thus a challenge, and in order to do so, evaluating the economic value of air quality is a crucial policy input. However, few studies accurately estimate this value as they neglect the dynamic and heterogeneous effects of air pollution.

Obtaining panel data from Beijing, China, the third chapter explores the two main research questions:

What is the effect of air quality on residents' welfare within the city? How do the effects change over time?

We, therefore, assess the economic effect of particulate matter with a diameter of 2.5 μm ($PM_{2.5}$) on housing prices in Beijing, China. As a proxy for housing prices, we use panel data comprising resale apartment transactions matched with average quarterly pollution data (i.e., $PM_{2.5}$) between 2013 and 2019. We used an instrumental variable (IV) approach to examine the housing price–$PM_{2.5}$ relationship through a hedonic framework. Our results show that households are willing to pay an extra 0.169% per housing unit price for an average quarterly reduction in $PM_{2.5}$ of 1 μg/m^3. The marginal willingness to pay (WTP) for improved air quality varies across income groups: People with high incomes were more willing to pay a premium for clean air than those with low incomes.

Chapter 4.

Chapter 4 examines the welfare effect of urban planning policy at the **policy and social dimensions,** and at the **inter-city level.** The rate of urban development depends not only on the city itself, but also on external forces such as strategies for regional integration. Such integration facilitates the exchange of labour and capital, the sharing of public resources, and a reduction in transportation costs. It also promotes cooperation among contiguous cities which further enhances inter-urban socio-economic interaction and accelerates inter-urban migration. Such cooperation could improve the quality of life in underdeveloped cities, but there is as yet very little research exploring the influence of inter-urban cooperation policy on residents' dwelling welfare, and even more so in underdeveloped areas.

This chapter assesses the effects of regional integration on housing prices to evaluate policy effectiveness for small and medium-sized cities on the peripheries of core cities. The key questions are:

How do urban housing prices change in the context of regional integration policy?

How do integration policies affect urban housing prices at different stages of integration?

Taking as a case study the Chinese city of Kaifeng – a contiguous city in the Zhengzhou megaregion – we use hedonic house price modelling and spatial econometrics to investigate the effect of Kaifeng's integration with the core city on the dynamics and determinants of housing prices between 2001 and 2016. The results show that housing prices in Kaifeng increased significantly after the city's integration with Zhengzhou in 2005. Results also confirm that regional integration had a significantly positive effect on housing prices, especially in border areas. Moreover, the new timesaving cross-border light rail system had more influence on the prices of nearby housing than the new expressway, and new urban districts with high-quality amenities led to a sharp rise in housing prices in Kaifeng.

Chapter 5.

Chapter 5 investigates the dynamic convergence of regional housing prices at the **economic and social dimensions**, and at the **regional level**. Next, enlarging our insights into the regional level, the dynamics of regional housing prices are used as a barometer for the equality of residents' welfare. The dynamics seem to vary across cities. Research suggests that urban housing prices will converge to different equilibria in a process known as club convergence. The formation of different groups of regional housing prices reflects differences in the socioeconomic, housing market, geographical, and urban amenity conditions offered by cities. So far, empirical evidence from developing countries on the existence of club convergence is limited.

This chapter focuses on the research questions:

Is there club convergence of regional housing prices in China's cities?

If so, what kinds of urban factors are the potential drivers?

Taking housing price trends of 70 major cities between 2006 and 2017, we detect club convergence in housing prices across Chinese regions and examine the determinants influencing club formation. A log *t*-test in combination with a clustering algorithm is used to assess club formation. The results show that regional housing prices face heterogeneous dynamics, providing some evidence of housing market segmentation. Four convergence clubs of Chinese regions with different convergence levels are identified. The ordered logit model shows that population growth, income, and housing regulation are among the drivers of club formation. Finally, being categorized in a different Chinese city tier as well as differences in urban healthcare also affect housing market club membership.

Table 1.1 Overview of chapters, research approach and publication outlet

Category	Title	Theoretical foundation	Econometric model	Key dimension of residents' urban welfare	Spatial scale	Journal	Authors
Chapter 2	Unearthing the value of wet markets from urban housing prices: Evidence from Beijing, China	Hedonic price theory	Spatial Error Model Quantile regression	Social and environmental	Intra-city	Habitat International (2022)	Yuanyuan Cai, Jinlong Gao
Chapter 3	Economic Valuation of Air Quality Change: Evidence from Housing Market in Beijing, China	Hedonic price theory	Panel fixed effects two-stage least squares (FE2SLS) model	Environmental	Intra-city	*Under review at a peer-reviewed journal*	Yuanyuan Cai, Martijn Smit, Marco Helbich
Chapter 4	Urban housing prices and regional integration: A spatial analysis in the city of Kaifeng, China	Hedonic price theory	Spatial Econometric Models; Differences in Differences across multiple cross-sections	Policy and social	Inter-city	Applied Spatial Analysis and Policy (2021)	Yuanyuan Cai, Yingming Zhu, Feng Yuan, Jinlong Gao, Marco Helbich
Chapter 5	Club convergence of regional housing prices in China: evidence from 70 major Cities	Regional convergence	Ordered logit regression	Economic and social	Region	The Annals of Regional Science (2022)	Yuanyuan Cai, Yingming Zhu, Marco Helbich

Chapter 2 Unearthing the Value of Wet Markets from Urban Housing Prices: Evidence from Beijing, China

This chapter is based on the article: Cai, Y., & Gao, J. (2022). Unearthing the value of wet markets from urban housing prices: Evidence from Beijing, China. Habitat International, 122, 102532.

ABSTRACT

Wet markets, recently thrust into the limelight during the coronavirus pandemic, play a necessary role in daily life in Asia. Yet despite their importance, the value of wet markets has not ever been explored. While an increasing body of work has studied the implicit value of urban public amenities through the hedonic price model and traditional measurements of accessibility and density, the subjective perceptions of amenities have been neglected, specifically for consumption amenity. This is especially the case with wet markets: traditional approaches are unable to capture their comprehensive effects. By employing data on Beijing housing transactions in 2019 and online review scores of wet markets, we reduce this knowledge gap by exploring both the amenity and dis-amenity effects of wet markets and capturing the objective and subjective perspectives. Our results indicate a nonlinear relationship between wet market accessibility and urban housing prices. Considering the perceived quality of wet markets, this paper further indicates that housing prices near high-scoring wet markets appreciate while housing prices depreciate near low-scoring markets. Interestingly, the negative influence of low-scoring markets is statistically larger than the positive influence of high-scoring wet markets. Taking the housing price as a reflection of an owner's wealth and income level, we argue that high-income dwellers tend to pay more for perceived quality than for convenience. Our findings therefore offer new and refined insights for scholars and urban planning decision-makers.

Keywords: Housing prices; Wet markets; (Dis)amenity; Accessibility; Perceived quality

2.1 Introduction

Wet markets (*cai shi chang*)[1] are open marketplaces spread widely across Asian cities. They are recognized as typical groupings of small vendors specialized in fresh and live products such as meat, fruits, vegetables, fish, and seafood (see Figure 2.1). As basic and essential living service spots for urban residents, wet markets are generally located close to densely populated communities and are favored by customers for convenience of proximity and the diversity of affordable food (Smith et al., 2014). For both shoppers and vendors, wet markets also act as centers of social interaction, particularly for the elderly. Some wet markets with local and traditional features, such as the *Sanyuanli Market* in Beijing and the *Bashi Market* in Xiamen, have even become popular scenic spots (Liu, 2020).

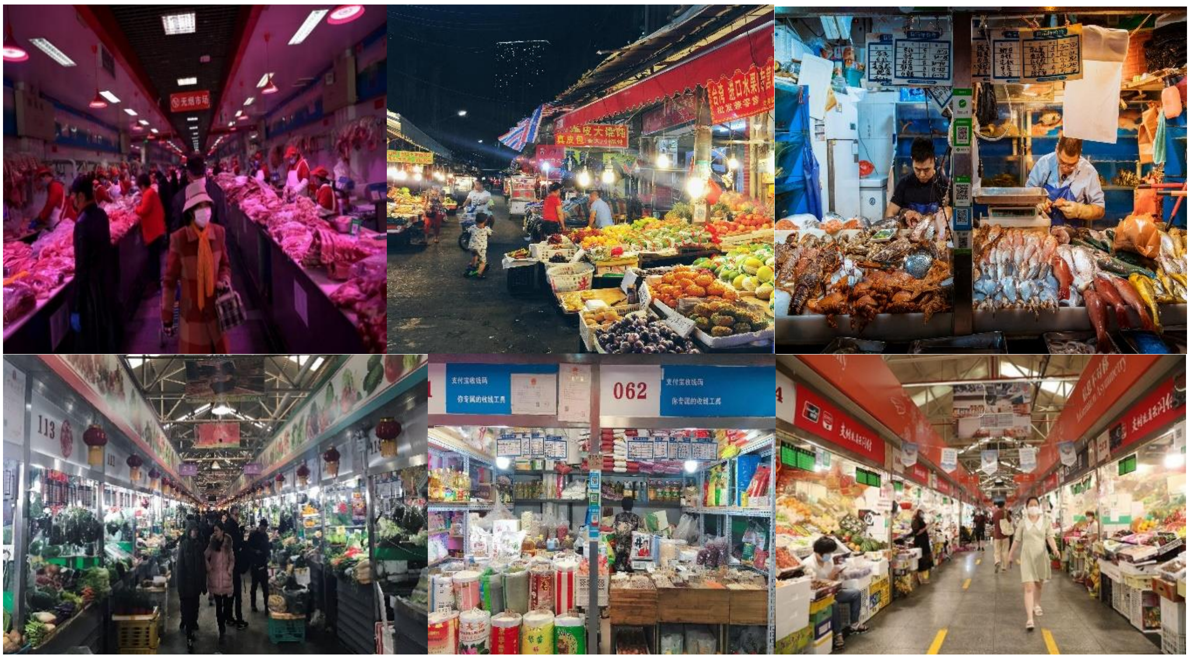

Figure 2.1 Wet markets in urban China(source: https://image.baidu.com/)

On the other hand, wet markets often feature less-desirable characteristics including over-crowding, slippery floors, poor ventilation, noise, and foul smells among others (Eiselt, 1995). As a result, wet markets are also sometimes regarded as sources of environmental nuisance (Bougoure & Lee, 2008; Si et al., 2019; Trappey & Lai, 1997). Moreover, the global COVID-19

[1] The term 'wet market' refers to markets with an abundance of produce—literally 'wet goods' in Chinese (湿货). At wet markets, water is used to keep seafood alive, vegetables looking clean, and chopping boards washed. In this sense, 'wet' is essentially a synonym for 'fresh.'

pandemic and its close association with wet markets (e.g., the *Huanan Seafood Market* in Wuhan or the *Xinfadi Wholesale Market* in Beijing) has recently amplified the negative perception of wet markets.

This two-sided nature implies that the effects of wet markets for residents and community welfare are rather complex. It is therefore essential to develop a framework that includes both the positive and negative effects of wet markets by unpacking the different elements of such value. We hereby try to fulfill this target by looking closer at wet markets—a type of urban facility— alongside housing prices in Beijing, China.

Stemming from the notion of amenities, a large body of literature has unveiled the impact of urban facilities on housing prices, which is widely considered to be a typical barometer of resident welfare (Hamilton & Morgan, 2010; Hu et al., 2014a; Song & Sohn, 2007). For instance, Imberman and Lovenheim (2016) and Wen et al. (2018) detected the capitalization of school quality in housing prices, while Yuan et al. (2020) took the nature of scarcity into consideration to demonstrate the differentiated influencing mechanisms of replaceable and irreplaceable amenities on housing prices . Though this line of research is fruitful and has documented the effects of urban facilities with single effects (either amenity or dis-amenity) on urban housing prices, limited attention has been given to the effect of those semi-obnoxious ones having both amenity and dis-amenity effects (Peng & Chiang, 2015).

In theory, the effects of semi-obnoxious facilities on housing prices may be nonlinear (Ohsawa & Tamura, 2003). Generally, the closer a facility locates, the easier its service can be accessed. Thus, residents are willing to pay more for the amenity, which can be suggested by purchased housing prices. However, residents may also have a higher possibility of suffering from dis-amenities such as noise and traffic jams (Chernobai et al., 2011; Debrezion et al., 2011; Zheng et al., 2020), which may on the other hand suppress surrounding housing prices. As Chernobai et al. (2011) and Chiang et al. (2015) argued, the distance to facilities matters for the magnitude and direction of the effect, and the dominant effect may change from amenity or dis-amenity to its opposite at a critical threshold distance. In this case, the nonlinear effect of access to wet market on housing prices is also something to be identified.

Given its nature of essential daily consumption and service facilities, accurately assessing the value of wet markets for residents by merely measuring the physical access and density using an implicit market model is difficult. Rather, the subjective perception of food quality and market environment is another important component of assessment (Luca, 2016; Meltzer & Schuetz, 2012). Therefore, combining the objective and subjective elements may be helpful in constructing a more precise and reasonable indicator, bridging the gap of the traditional distance-density approach (Kuang, 2017). Thanks to recent advances in big data, urban science scholars have generated creative variables and improved measurement approaches (Glaeser et al., 2018). The digitization of user-generated information, such as online customer reviews and scores, can be employed to effectively assess the quality of amenities by capturing the subjective perceptions of residents (Kang et al., 2020).

Furthermore, the effect of urban amenities may vary across different housing submarkets and social cohorts. For instance, high-income dwellers are willing to pay more for clean air than those with relatively low incomes (Chen et al., 2018). Different homebuyer characteristics may also lead to different urban amenity preferences (Bakis et al., 2019; Hitaj et al., 2018). As such, one could expect a large difference among homebuyers at different income levels in their preferences for wet markets. Thus, it is worth providing empirical evidence for this assumption. Employing spatial hedonic price models and Beijing's 2019 housing data, we detect the relationship between wet market and urban housing prices. Regarding our potential contribution, this study offers one of the few, if not the first, explorations on the value of wet markets for urban residents. Based on housing prices, we build a conceptual framework market to dissect the relationship between wet markets and community welfare from two opposite aspects (e.g., the amenity and dis-amenity effects), and test the nonlinear effect of access to wet markets on housing prices. Also, we refine the accurate value of wet markets by capturing comprehensively objective and subjective perceptions through combing the physical accessibility and the big data of online customer reviews.

The paper proceeds as follows. After presenting the conceptual framework we built in Section 2, we describe the datasets, the measured indicators and regression models in Section 3. Section

4 presents the empirical results. The research significance and policy implications are discussed in Section 5 and Section 6 concludes.

2.2 Conceptual framework

Based on Rosen's (1974) hedonic price framework, the price of real estate is determined by both internal characteristics of the property itself (e.g., housing structure and age, and floor area) and external factors (e.g., neighborhood environment, location, and so on). This means that the value of nearby facilities—including the wet market—has been capitalized into property values. Hence, an evaluation of the effects of wet markets for residents can be based on housing prices.

Making up approximately 73% of the market share of fresh food,[2] China's wet markets are the main retail outlet for fresh food purchases (Maruyama et al., 2016). As a result, wet markets play an important role in China by providing daily convenience and opportunities for social bonding for residents. In fact, as Si et al. (2019) documented, given the advantages in availability, affordability, and accessibility, wet markets prevail for fresh produce and meat purchases. Additionally, different vendors normally provide a range of alternatives for products. Location is also critical for purchasing convenience (Hino, 2010). Because the widely promoted 15-minute Community-life Circle scheme[3] aims to offer convenience and improved quality of life for residents in urban China, wet markets tend to be distributed near communities (Z. Li et al., 2019). Alongside convenience, the bustling vitality (*yanhuoqi*) of wet markets generate additional and positive socio-cultural effects including strengthened community ties, increased residential wellbeing and satisfaction, and increased visitors. Shopping in a wet market can satisfy a customer's shopping habits and preferences related to selecting, comparing, and bargaining (Liu, 2020). Wet markets also act as a public space in which bonding through informal social interactions takes place. Neighbors have opportunities to encounter and communicate across different social groups and so enhance feelings of community identity (Mele et al., 2015). Through regular visits and purchases, customers and vendors form special

[2] Source: https://www.sohu.com/a/320524056_99900352

[3] In this scheme, which aims to meet the basic living needs of residents and improve urban serving capability, basic functional facilities are located within reasonable (e.g., 15 minutes) walking distance.

social connections and build long-lasting and reciprocal relationships, which could in turn enhance food quality (Maruyama et al., 2016; Zhong et al., 2020). Recognized as the amenity effect including accessibility and good subjective perception from purchase experience and social interaction, wet markets therefore may imply housing prices in nearby neighborhoods are at a premium.

On the other hand, several other issues associated with wet markets, such as poor or unfavorable shopping environments and services, have led to a countervailing dis-amenity effect (or external negative effect). First, most traditional wet markets are located in cramped, narrow spaces, inappropriately planned primarily by urban planner. In addition, wet market stalls are generally rented by private street vendors which makes market supervision difficult for market manager. Possible reasons are that most vendors have low educational levels, stores are cluttered and soiled, and services are poorly regulated (Bougoure & Lee, 2008). Moreover, two to three shopping peaks per day means that areas both in and around wet markets are often crowded and noisy, which is a nuisance for nearby residents. Last but not least, selling and slaughtering 'wet' items like live poultry, seafood, and even wild animals in humid wet market environments may cause a risk to human health through the spread of zoonotic diseases such as COVID-19 and SARS (Aguirre et al., 2020). All of these negative aforementioned factors of wet markets may offset their amenity effects, and should largely decrease housing prices in nearby communities.

Given the above discussion, we developed a conceptual framework to capture both opposing effects. As Figure 2.2 shows, we expect amenity effects to raise housing prices while dis-amenity effects would lower prices. We also expect that the extent of these effects might vary across space; impacts could consequently be heterogeneous across communities as well. The aim of the present work was therefore to detect the two effects of wet markets on housing prices. Accurately unpacking the effects of wet market might help in formulating urban planning projects and market management regulations.

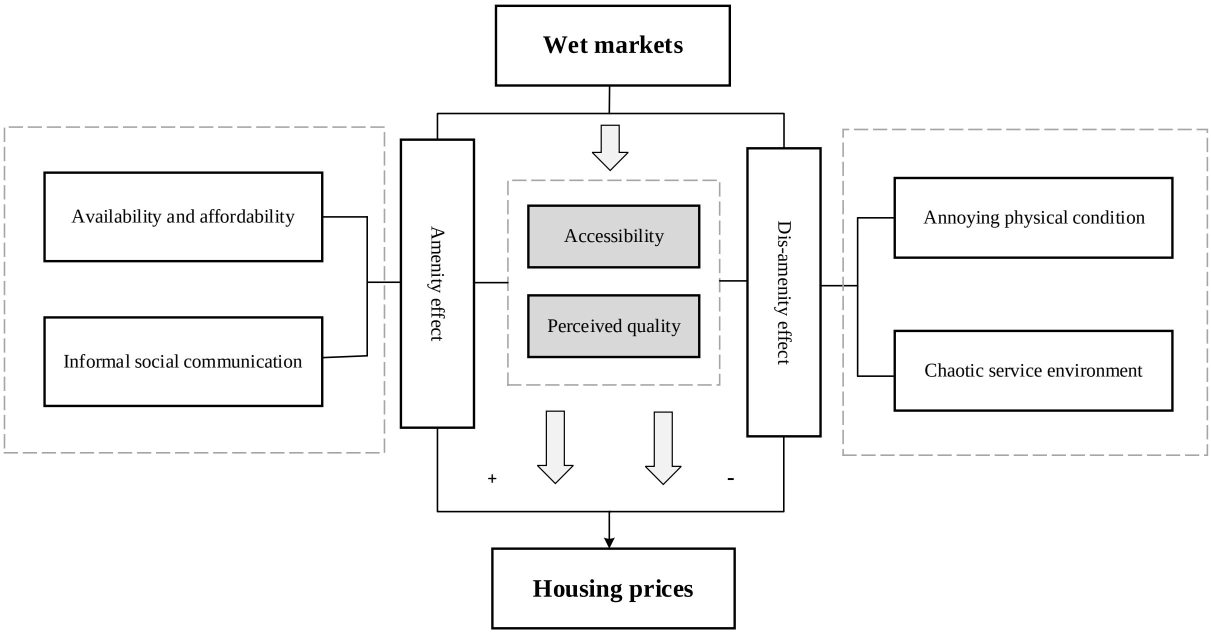

Figure 2.2 Conceptual framework of wet market influence on urban housing prices

2.3 Empirical approach

2.3.1 Study area

Beijing was chosen for our empirical case study. The city has a total land area of 16410.54 km^2 and a population of 21.89 million, 38.5% of which are immigrants (Communiqué of the Seventh National Population Census, 2021). This diversity of population may result in various consumption demands. As one of the most developed cities in China, Beijing has relatively complete public services that are sponsored by the state and can easily meet almost all resident needs. Moreover, Beijing's housing market is well developed and can be divided into several submarkets (Sun et al., 2017) which makes it an ideal case to explore the real value of wet markets for residents.

2.3.2 Data collection and processing

This study is based on three sets of data: 1) housing transaction data; 2) location and neighborhood attributes; and 3) wet market reviews.

2.3.2.1 Housing data

We collected the transaction data of residential dwellings spanning the whole of 2019 (including housing characteristics such as prices and addresses) from Homelink (bj.lianjia.com/)—one of the biggest real-estate brokerages in China—to detect the response of the housing market. Next, a database was compiled with the use of basic housing information from dwellings in urban Beijing (Figure 2.3) including address, floor (or level), floor area, building type, and housing age among others.

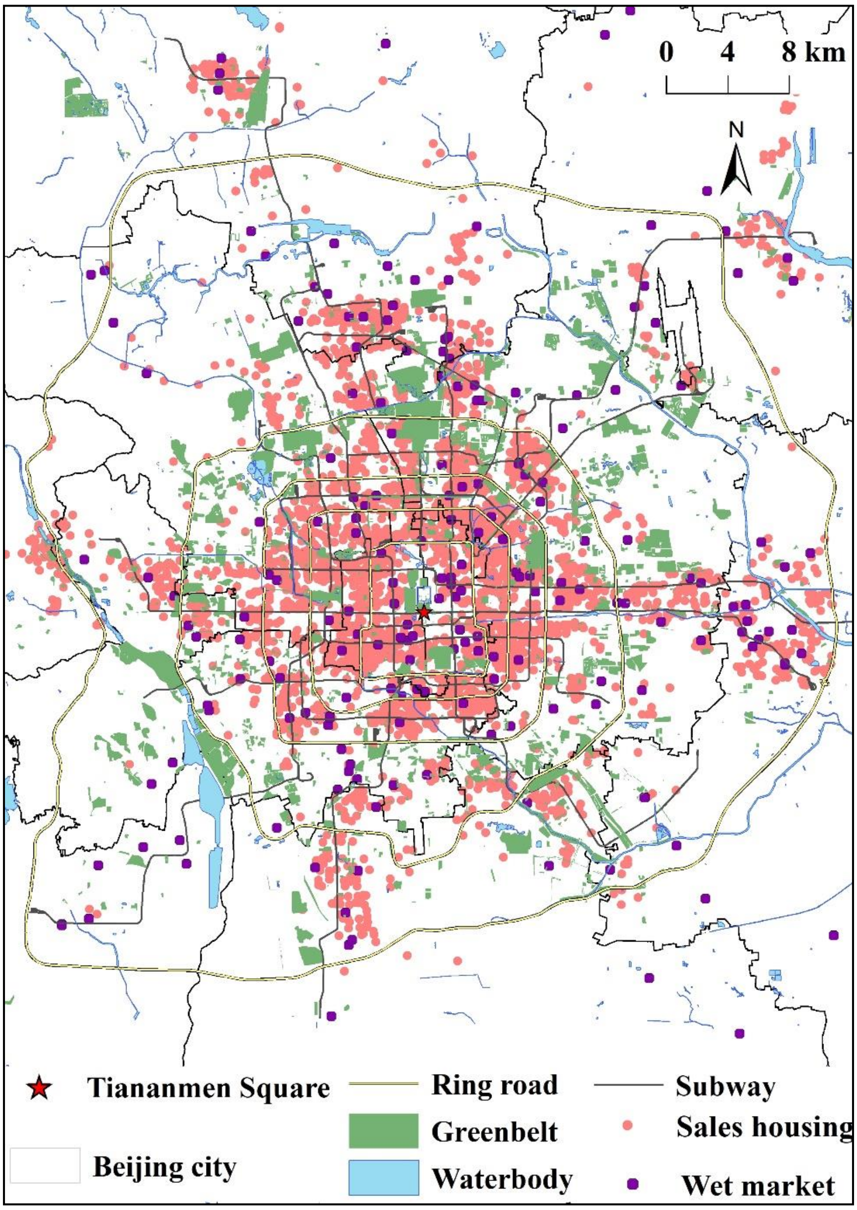

Figure 2.3 Spatial distribution of housings and wet markets in Beijing based on the study sample

2.3.2.2 Location and neighborhood characteristics

The second dataset is based on points of interest (POIs) extracted from Amap (amap.com/). Specifically, location factors including distances from communities to the nearest urban center or sub-centers, bus stops, subway stations, and shopping malls were measured. We also considered neighborhood factors such as distances from dwellings to the nearest key primary schools, comprehensive 'Triple A' hospitals,[4] urban parks, and local government offices as well as daily need and leisure services within one kilometer (km). Further, we obtained community population densities from WorldPop (worldpop.org/) with a spatial resolution of 100m×100m. Using Geographical Information System (GIS) techniques, we associated these attributes with the first dataset and finally get the matched information of 4353 housing points in urban Beijing. Table A 2.1 in the appendix defines all variables in detail while Table A 2.2 provides a summary for both dependent and independent variables.

2.3.2.3 Review data from Dianping.com

To account for the perceived quality of wet markets, we used Dazhong Dianping (dianping.com/) to leverage online wet market reviews from Yelp and TripAdvisor. As a result, we derived the names, addresses, and review scores and counts of a total of 307 wet markets. Using Google Earth software, we then georeferenced these wet markets on a digital map of Beijing and matched them with the housing in our sample (Figure 2.3). Next, we obtained a comprehensive review score from the score-weighted value from three perspectives of taste, environment, and service across all reviews for each wet market. The score is rated from 0 to 5 with a 0.1 score increment. Table 2.1 presents the descriptive statistics of reviews.

Table 2.1 Descriptive statistics of wet market reviews

Name	Mean	Std Dev	Min	Max
Review score	3.769	0.334	3.27	4.89
# Taste score	3.779	0.331	3.2	4.86
Environment score	3.731	0.287	2.97	4.82
Service score	3.734	0.365	2.76	4.84
Review count	75.06	265.43	10	4199

2.3.3 Operationalization of wet market properties

Based on our conceptual framework presented in Section 2, we discussed the different indicators necessary to uncover (dis)amenity effects. First, accessibility to and proximity of wet

[4] 'Triple A' hospital refers to hospitals that have been awarded the highest among three grades based on: the level of service provision; size; medical technology equipment and quality; and management.

markets were used to evaluate the amenity effect given the distance decay nature of the (dis)amenity effect of public facilities. Second, an aggregated indicator combining customers' subjective perception of the shopping environment and the accessibility of wet market was as a proxy variable of the perceived amenity quality that directly affects consumption activities (Charreire et al., 2010; Clarke et al., 2002).

According to studies on the 15-minute Community-life Circle (Zhong et al., 2018), 1500 meters (m) is an acceptable distance for residents to bicycle or travel on foot.[5] We hence evaluate the effect of nearby wet markets on the housing market by identifying wet markets within a 1500 m range from each dwelling within our sample and recording the respective Euclidian distances.

2.3.3.1 Measures of wet market accessibility

Following conventional accessibility indices by Bhat et al. (2000) and Kuang (2017), the accessibility measure ACC_i is constructed as the distance weighted number of wet markets, where each successful match between dwelling i and nearby wet market j is weighted inversely to the θ^{th} power of its Euclidian distance:

$$ACC_i = \sum_{j=1}^{W_i} \frac{d_{i,j}}{dist_{i,j}^{\theta}} \quad (1)$$

W_i denotes the total number of wet markets within a range of 1500 m from dwelling i. A successful match between dwelling i and nearby wet market j within the radius is indicated by $d_{i,j}$=1, while unsuccessful matches are recorded as zeros. The effects of local consumption amenities associated with surrounding wet markets are assumed to decrease with greater distances. In the baseline case, θ is equal to *1/2*. ACC_i is the distance weighted number of neighborhood wet markets for dwelling i, without distinguishing the amenity level of each wet market.

Given that the amenity and dis-amenity effects are closely correlated with distance, we also computed the proximity of wet market (Dis_wetmarket, or the distance from dwelling to the

[5] Results remain robust with different radii such as 1000 m and 2000 m.

nearest wet market) to offer the robustness test. Furthermore, to capture the aforementioned nonlinear effect (both amenity and dis-amenity effects) of wet markets, we also include the Quadratic terms Dis_wetmarketsq and *ACCsq* in the models.

2.3.3.2 Measures of perceived wet market quality with reviews scores (ACCH, ACCL)

The reported Dianping scores and ratings are aggregated across all scores and ratings submitted by reviewers and are given based on their level of satisfaction with the consumption experience. The review information conveys information on a perceived wet market amenity, which facilitates a distinction between high-scoring and low-scoring wet markets for new customers. Given that the average Dianping rating for the wet market is just above 3.5 stars, we chose review scores as our evaluation index to distinguish the deviated quality between wet markets; the average score is roughly 3.7. Housing from our sample with a score of 3.7 or more are placed in the high-score group which is indicated by $h_j = 1$ while those with a score of less than 3.7 are classified into the low-score group which is indicated by $l_j = 1$. Measures of the distance-weighted number of wet markets with high versus low scores were constructed as above:

$$ACCH_i = \sum_{j=1}^{W_i} \frac{d_{i,j} * h_j}{dist_{i,j}^{\theta}} \quad (2)$$

$$ACCL_i = \sum_{j=1}^{W_i} \frac{d_{i,j} * l_j}{dist_{i,j}^{\theta}} \quad (3)$$

These two measures of perceived amenity constitute the decomposition of accessibility for the two high-scoring and low-scoring markets. Table 2.2 presents a summary of the above measured indicators of wet markets.

Table 2.2 Statistical description of multiple indicators of wet market

Variable	Definition	Mean	Std Dev	Min	Max
Dis_wetmarket	Logarithm of distance to nearest wet markets	7.074	0.799	-0.222	9.130
Dis_wetmarketsq	Quadratic term of Dis_wetmarket	50.68	10.38	0.023	83.36
ACC	Accessibility to wet markets	0.055	0.027	0.026	0.597
ACCsq	Quadratic term of ACC	0.004	0.009	0.001	0.356
ACCH	Accessibility to high-scoring wet markets	0.033	0.027	0	0.576

ACCL	Accessibility to low-scoring wet markets	0.036	0.028	0	0.584

2.4 Methodology

2.4.1 Hedonic price model

We first set the standard hedonic price model as our baseline to examine the comprehensive implicit value of wet markets, including both amenities and dis-amenities with the following formula:

$$HP_i = \alpha + \sum_k r^k M_i^k + \beta X_i + \varepsilon_i \quad (4)$$

Here, HP$_i$ is the logarithm of the unit sale price for dwelling i while α is the regression constant. M_i^k denotes the measure of wet market accessibility for dwelling i as defined in section 3.3.3 (*i.e.*," $k \in \{ Dis\_wetmarket;\ Dis\_wetmarket, Dis\_wetmarketsq;\ ACC;\ ACC, ACCsq;\ ACCH, ACCL" \}$) and γ^k is the coefficient we estimate that shows the latent impact of the variable k of wet market on housing prices. X is a vector of a series of housing structures and locational and neighborhood characteristics for dwelling i, and β is the vector of coefficients. ε is an error term capturing unobserved factors.

2.4.2 Spatial hedonic model

Ordinary least squares (OLS) estimation ignores the potential spatial interaction effects such as spatial dependence, autocorrelation, and heterogeneity, and may cause the estimators to be biased (Anselin, 2013). Hence, spatial econometric models including spatial lag, spatial error, and spatial Durbin models are widely used instead (Anselin, 2010). Similarly, as spatial model techniques are also embedded in the hedonic model, the spatial hedonic model becomes an efficient and popular tool to address spatial issues in the determinant analysis of housing prices (Anselin & Le Gallo, 2006; Sohn et al., 2020).

The significant Moran's I statistics of the OLS residuals[6] (e.g., Moran's I = 0.482, P = 0.000 for *ACC*; Moran's I = 0.481, P = 0.000 for *ACCH* and *ACCL*) indicates the positive spatial

[6] Each k model with different measurement types of wet market amenities performs the tests of Moran's I and the LM.

dependency across housing price residuals. As known, the mixed regressive-spatial lag model (mixing a spatially lagged dependent variable with a spatially autocorrelated error term), spatial autoregressive model (SAR, spatial dependence in the dependent variables), and spatial error model (SEM, spatially correlated errors) are generally adopted to control spatial autocorrelation effects (Elhorst, 2010). To identify which model was optimal for our research, we adopted Lagrange multiplier (LM) tests to detect whether spatial lag (LMLAG) and errors (LMERR) existed (Anselin, 2013). Given the significance of both tests, robust statistical tests (i.e., R-LMLAG and R-LMERR) were performed. The only significant Robust LM-err statistics mean the SEM model is recommended for our analyses; thus, we report the corresponding results. The formula can be specified as follows:

$$HP_i = \alpha + \sum_k r^k M_i^k + \beta X_i + \mu_i, \quad u_i = \lambda \sum_j W_{ij}\mu_j + \varepsilon_i \qquad (5)$$

Here, λ is the spatial autocorrelation coefficient and W_{ij} are the elements in the i^{th} row of a spatial weight matrix, $W_{ij}\mu_j$ represents the interactive effects among the error lag terms of the spatial units *i* and *j*, and ε_i is assumed to be *iid* standard normal.

The graph-based weight matrix method was employed to create the weighted matrix with housing points shapefile by R software, *W*, which is an adequate approach for the representation of information exchange (Matula & Sokal, 1980). Meanwhile, Distance-based weights including *k*-Nearest neighbors (setting $K = 6$) or Distance-band weights (i.e., distance = 9000 m) were also tested. In contrast, the graph based on the weight matrix method provides a better fit for the models and showed statistically significant parameters with theoretically consistent signs. Thus, we chose the graph based on weight matrixes to perform the spatial regression analysis in *R* software.

2.5 Results

Results of the regression estimations are presented in Tables 2.3–2.5. The signs on housing structure characteristic variables that we included as controls are mostly in line with previous research. New slab-type houses with southern orientation, refined decoration, more bedrooms, and elevators sell at the higher prices. Neighborhood amenities including schools, hospitals, pleasant landscapes, parks, and leisure services contribute to higher prices, while daily needs businesses, such as barber shops and laundries, depreciate housing prices. Location attributes such as distances to urban centers and subway stations facilitate higher housing prices, while bus stations depreciate nearby housing prices. The significance of the control variables reassures us that we have taken the standard predictors of housing prices into account. Hence, we focus mainly on our variables of theoretical interest: the coefficients of wet market variables.

2.5.1 Wet market accessibility matters

Table 2.3 presents the regression results of the linear and nonlinear effects related to the accessibility of wet markets on urban housing prices. The first two columns illustrate the linear results of the OLS and SEM models, while the remaining two columns present the nonlinear results following the same methods. Prior to the construction of the models, we tested the variance inflation factors (VIFs) of each independent variable to find that all VIFs are smaller than 3, indicating that there are no serious multicollinearity problems in the models. The adjusted R-squared values of 0.569 and 0.570 in OLS regressions imply that our models fit well, based on the chosen variables and model form. The higher Log-Likelihood indices and lower Akaike Information Criterions (AICs) of SEM compared to the SAR models (Linear: 75.181, Non-linear: 75.137) justify the better fitness of the former than the latter.

Coefficients of the ACC variable in linear models (both OLS and SEM) indicate a negative relation with the accessibility to wet markets on urban housing prices. The coefficient in SEM can be interpreted to mean that housing prices would decrease by 24.9% with each one-unit increase of accessibility to wet markets. This provides evidence for our hypothesis that the dis-amenity of wet markets indeed discounts nearby housing prices and echoes similar findings on the effect of retail markets (Cai et al., 2021; Jang & Kang, 2015; Yuan et al., 2018).

Further, the nonlinear effect is found by adding the $ACCsq$ variable to the OLS and SEM models, as the quadratic term ACC. The positive coefficients of $ACCsq$ with a 90% significance level and the negative coefficients of ACC with a 99% significance level indicate a nonlinear relationship between the accessibility to wet markets and urban housing prices (see Figure B 2.1). That is, the influence of accessibility to wet markets on urban housing prices would change from restraint toward promotion with increasing distance. Specifically, the dis-amenity effect of wet markets is greater than the amenity effect on residents in the range closer to the market; the amenity effect would become dominant beyond a certain threshold of distance with the bad influence gradually diminishing. In essence, it is the trade-off between convenience and nuisance when dwellings are adjacent to wet markets. In some cases, the accessibility benefits of being adjacent to wet markets would be offset somewhat by the dis-amenity associated with proximity. These findings confirm our hypotheses concerning both the dis-amenity and amenity effects of wet markets, which is similar to the dual effects (*i.e.,* positive and negative) of public transport on housing prices (Seo et al., 2014).

To ensure the robustness of the results, a sensitivity check was conducted by way of the spline regression with substitute variables Dis_wetmarket and Dis_wetmarketsq. Table A 2.3 in the appendix shows the negative and positive effects of Dis_wetmarket and Dis_wetmarketsq respectively, which also offers evidence for the amenity and dis-amenity effect of wet markets.

Table 2.3 Estimation results of the linear and nonlinear effects of accessibility to wet markets

	Linear effect		Nonlinear effect	
	OLS	SEM	OLS	SEM
ACC	-0.481***	-0.249**	-0.905***	-0.379***
	(0.170)	(0.166)	(0.275)	(0.318)
ACCsq			1.529*	0.338*
			(0.781)	(0.707)
Structure	√	√	√	√
Location	√	√	√	√
Neighborhood	√	√	√	√
Constant	15.031***	14.684***	15.055***	14.692***
	(0.180)	(0.208)	(0.181)	(0.209)
N	3,376	3,376	3,376	3,376
Adjusted R^2	0.569		0.570	
Log-Likelihood		402.450		402.564
AIC		-742.901		-741.129
LR Test		1,189.207**		1,185.572***
Wald Test		1,568.725***		1,565.342***

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For brevity, the coefficients for housing structure characteristics, neighborhood characteristics and locational control variables are not reported.

2.5.2 The perceived quality of wet markets matters

As Table 2.4 shows, the subjective perception information from consumers has a distinct effect on housing prices, apart from the objective accessibility. The opposite coefficients of $ACCH$ and $ACCL$ suggest a positive association with wet markets scored above 3.7 and a negative association with their lower-scoring counterparts (i.e., below 3.7) with nearby housing markets, which verifies our hypothesis. More specifically, the coefficients of $ACCH$ and $ACCL$ in the SEM indicate that housing prices tend to rise by 1.1% with each one-unit increase of distance to reputable markets. On the contrary, housing located close to poorly evaluated wet markets suffer a 28.3% market depreciation. Obviously, the depreciation rate of housing prices caused by wet markets with relatively lower scores is greater than the appreciation rate of high-scoring ones, justifying the conclusion that the dis-amenity effect (or external negative effect) of wet markets, such as poor environment and bad-quality service, can easily offset the amenity effect (or internal positive effect). This might also be a result of the rise of the alternative retail food outlets, including supermarkets, hypermarkets, and modern fresh supermarkets as well as the advancement of e-shopping (Si et al., 2019).

Table 2.4 Estimation results of the perceived effect of wet markets

	OLS	SEM
$ACCH$	0.086**	0.011**
	(0.167)	(0.105)
$ACCL$	-0.634***	-0.283***
	(0.163)	(0.192)
Structure	√	√
Location	√	√
Neighborhood	√	√
Constant	15.045***	14.690***
	(0.180)	(0.208)
N	3,376	3,376
Adjusted R^2	0.570	
Log Likelihood		402.406
AIC		-740.812
Wald Test		1,560.250***
LR Test		1,181.206***

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For brevity, the coefficients for housing structure characteristics, neighborhood characteristics and locational control variables are not reported.

2.5.3 The (dis)amenity effects of wet markets across income groups

In general, the willingness to pay for urban amenities varies between consumers with different backgrounds including income and education levels (Fernandez & Bucaram, 2019; Yang et al., 2020). We thus conducted a quantile regression to explore the possible heterogeneity of wet market impact on housing prices across different social cohorts by dividing houses in our sample into four groups: low, middle-low, middle-high, and high quartiles. Table 2.5 presents the estimated coefficients of accessibility to and perception of wet markets with other variables being controlled. For accessibility, the significantly negative coefficients for housing prices in Q50 (-1.107), Q75 (-1.590), and Q90 (-1.872) indicate that housing prices would be discounted by wet markets with more serious discounts in groups with higher housing prices. That is, dwellers purchasing higher-priced houses care more about the dis-amenity effect of wet markets. This can be further implied by the negative significance of the variable of *ACCL* in the Q50, Q75, and Q90 groups. If the premise that housing price is an indicator of income level makes sense, high-income residents tend to pay more attention to the quality perception of wet markets including food quality, physical environment, and service rather than convenience. Because they have more travel and shopping options, high-income residents care less about the physical distance to wet markets.

Table 2.5 Quantile regression results of the social heterogeneity of wet markets

	Accessibility			
	Q25	Q50	Q75	Q90
ACC	-0.322	-1.107***	-1.590***	-1.872**
	(0.360)	(0.346)	(0.460)	(0.844)
ACCsq	0.818	1.713**	2.322	2.484
	(1.747)	(2.154)	(6.183)	(1.030)
Structure	√	√	√	√
Location	√	√	√	√
Neighborhood	√	√	√	√
N	3,392	3,392	3,392	3,392
Adjust-R^2	0.3715	0.3965	0.3750	0.3328
	Perceived quality			
	Q25	Q50	Q75	Q90
ACCH	0.263	-0.0130	-0.200	-0.162
	(0.200)	(0.116)	(0.164)	(0.368)
ACCL	-0.223	-0.845***	-0.895***	-1.049***
	(0.184)	(0.109)	(0.286)	(0.336)

Structure	√	√	√	√
Location	√	√	√	√
Neighborhood	√	√	√	√
N	3,392	3,392	3,392	3,392
Adjusted-R^2	0.3723	0.3973	0.3755	0.3351

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For brevity, the coefficients for housing structure characteristics, neighborhood characteristics and locational control variables are not reported.

2.6 Discussion

As daily consumption and communication centers for residents in Asian cities, wet markets play multiple roles that generates complex effects on residents' welfare. Though the spotlight has shined on wet markets since the outbreak of COVID-19, the specific value of wet markets has not been sufficiently explored in general, and particularly for those Westerners who are unfamiliar with this Asian-origin facility. Methodologically, an increasing body of literature has produced regarding the amenity effects of urban facilities (e.g., schools, parks, traditional landscapes, retail stores, and restaurants) with the help of the conventional hedonic price model. However, this conventional approach based on physical distance and density measures can hardly reflect the actual effects of facilities with dual-impacts given the fact that residents' subjective perception for these consumption amenities matters.

With respect to our contribution, this work, to our best knowledge, is one of the few studies on the value of wet markets for residents, which may have potential in better our understanding on the complex effects of semi-obnoxious facilities. In theory, this paper constructs a conceptual framework for the impact of wet markets on housing prices from both amenity and dis-amenity aspects. This helps to unravel the underlying impetus of the complex effects and enables the provision of a theoretical reference for a follow-up research of similar facilities. Furthermore, we construct an aggregated indicator of wet markets by combining the physical accessibility with reviewer online score to capture the effect of wet markets from both objective and subjective perspectives. This extends the analyzing insight and refines the measurement, which may also provide a methodological reference for assessing the values of consumption amenities with similar attributes such as museums, restaurants, and other leisure services.

From a policy perspective, previous studies assess the food environment with accessibility and density indicators and compel decision-makers to recognize 'food deserts' within cities, which refers to disparities in food distribution (Bader et al., 2010; Sparks et al., 2011). The findings of this present work offer some new and refined implications for decision-makers in retail food planning as well as for efficient market management. Specifically, the nonlinear relationship between the accessibility to wet markets and housing prices calls for the reasonable location of new markets where the maximum amenity effect can be achieved with the dis-amenity effect being minimized. Equally, and if not more significantly, our results indicate the importance of improving the quality of markets in terms of food quality, the physical environment, and service, given that residents—particularly residents with high incomes—are more sensitive to nuisances than the amenity effect of wet markets. Evidently, the COVID-19 pandemic is an additional caveat to consider when it relates to the environmental condition of wet markets.

However, several limitations in our study could be improved in future research. First, although we control the possible spatial effect of housing prices, the cross-sectional data in our study might limit the capture of the comprehensive influence of wet markets such as the long-run effects of wet market (Hsiao, 2014). Thus, collecting panel data is a critical prerequisite for further research. Second, the rapid development of supermarkets, coupled with the mushrooming of fresh supermarkets, means that wet markets are no longer indispensable in the daily lives of residents. These modern food retailing formats increasingly compete with wet markets and so would, to some extent, grab the welfare value of wet markets (Goldman et al., 1999). Bearing these trends in mind, it is of great importance to explore the replacement effect of new retail formats for wet markets and thus to address the possible issue of overestimating the effects of wet markets.

2.7 Conclusion

Taking Beijing as an example, we gauged the value of wet market from urban housing prices. We linked data on 2019 housing transactions to information on wet market review scores collected from *Dianping.com*; we then calculated the accessibility to and perceived quality of wet markets. Considering the potential spatial dependence effect, we employ the spatial error model (SEM) to examine both amenity and dis-amenity effects of wet markets as well as to further analyze the heterogeneity of wet markets' impact on housing prices across different income cohorts with quantile regression.

Some findings are presented in our paper. First, the results of the nonlinear models suggest a nonlinear relationship between the accessibility to wet markets and housing prices. That is, the dis-amenity effect dominates in places close to wet markets and somewhat depreciates housing prices there. With increasing distance from wet markets, the negative influence gradually declines and changes to positive beyond a certain threshold of distance. This reflects the trade-off between wet market convenience and nuisance in the housing market. Second, by adding the perceived quality of markets to the hedonic model, we further detect the perceived effect of wet markets with consumers' online review scores and find that quality matters more than accessibility. Interestingly, the negative influence of lower-scoring wet markets is statistically larger than the positive influence of higher-scoring wet markets. Moreover, taking the housing price as a reflection of an owner's wealth and income level, we find, with the help of the quantile regression model, that higher income earners tend to pay more for the perceived quality than convenience.

2.8 Appendix

2.8.1 Appendix A

Table A 2.1 Definition and calculation of variables

Category	Variable	Definition and calculation
Dependent	HP	Logarithm of housing price per square meter (Yuan/m^2).
Structure characteristics	Floor	Dummy variable. Floor1=top, Floor2=high, Floor3=middle, Floor4=low, Floor5=ground.
	Floor area	Logarithm of floor areas.
	Building type	Dummy variable for building type. BT1=slab-type, BT2=a mix of slab and tower type, BT3=tower-type.
	House age	Logarithm of housing age.
	Orientation	Dummy variable. 1=apartments with southern orientation; 0=otherwise
	Decoration	Dummy variable. Dec1=refined decoration, Dec2= simple decoration, Dec3= roughcast.
	Bedroom	Number of bedrooms.
	Elevator	Dummy variable. 1=apartment with an elevator; 0=otherwise.
Location features	Dis_CBD	Logarithm of distance to the nearest urban center or subcenters, namely Tiananmen Square, Jianguomen CBD, Beijing Financial Street (BFS), Zhongguancun Science Park (ZSP), and Olympic Park.
	Dis_Bus	Logarithm of distance to nearest bus stop.
	Dis_Subway	Logarithm of distance to nearest subway station.
	Dis_Shoppingmall	Logarithm of distance to nearest shopping mall.
Neighborhood attributes	Pop	Logarithm of population density per community (person/100m^2).
	Dis_School	Logarithm of distance to nearest key primary school.
	Dis_Hospital	Logarithm of distance to class 3A hospital.
	Dis_Landscape	Logarithm of distance to nearest pleasant landscape.
	Dis_Park	Logarithm of distance to nearest city park.
	Dis_Government	Logarithm of distance to nearest local government office.
	Num_Dailyneeds	Logarithm of number of service shops, including barber shops, post offices, telecom business halls and laundries, *etc.* within 1000 m based on the 15-min walking community.
	Num_Leisureservice	Logarithm of number of leisure places including karaoke venues, bars, museums, gyms, and others within 1000 m.

Table A 2.2 Descriptive statistics of the variables

Category	Variable	Mean	Std Dev	Min	Max
Dependent	HP	11.05	0.397	9.339	12.39
Structure characteristics	Floor1	0.399	0.490	0	1
	Floor2	0.203	0.402	0	1
	Floor3	0.185	0.388	0	1
	Floor4	0.113	0.316	0	1
	Floor5	0.101	0.301	0	1
	Floor area	4.377	0.436	2.909	6.489
	BT1	0.227	0.419	0	1
	BT2	0.151	0.358	0	1
	BT3	0.623	0.485	0	1
	House age	3.010	0.472	1.386	4.248
	Orientation	0.650	0.477	0	1
	Dec1	0.398	0.489	0	1
	Dec2	0.362	0.481	0	1
	Dec3	0.223	0.416	0	1
	Dec4	0.0175	0.131	0	1
	Bedroom	2.170	0.810	1	8
	Elevator	0.517	0.500	0	1
Location features	Dis_CBD	8.867	0.808	3.438	10.80
	Dis_Bus	5.938	0.902	-1.762	8.815
	Dis_Subway	7.095	0.879	-0.0889	10.250
	Dis_Shoppingmall	6.830	0.869	-3.636	9.356
Neighborhood attributes	Pop	4.668	0.948	0.365	7.022
	Dis_School	7.812	0.833	2.981	10.610
	Dis_Hospital	7.720	0.909	2.146	10.64
	Dis_Park	7.355	0.659	2.621	9.204
	Dis_Landscape	6.155	0.884	-0.215	8.354
	Dis_Government	4.397	1.462	-4.787	7.908
	Num_Leisureservice	4.131	0.804	0	5.994
	Num_Dailyneeds	4.788	0.769	0	6.326

Table A 2.3 Robustness check for the nonlinear effect based on wet market proximity

	OLS	SEM
Dis_wetmarket	0.107***	0.093***
	(0.028)	(0.028)
Dis_wetmarketsq	-0.011***	-0.010***
	(0.002)	(0.002)
Structure	√	√
Location	√	√
Neighborhood	√	√
Constant	15.177***	14.960***
	(0.167)	(0.180)
N	4,231	4,253
Adjusted R^2	0.567	
Log Likelihood		-281.304
AIC		626.609
Wald Test		54.963***
LR Test		54.394***

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For brevity, the coefficients for housing structure characteristics, neighborhood characteristics and locational control variables are not reported.

2.8.2 Appendix B

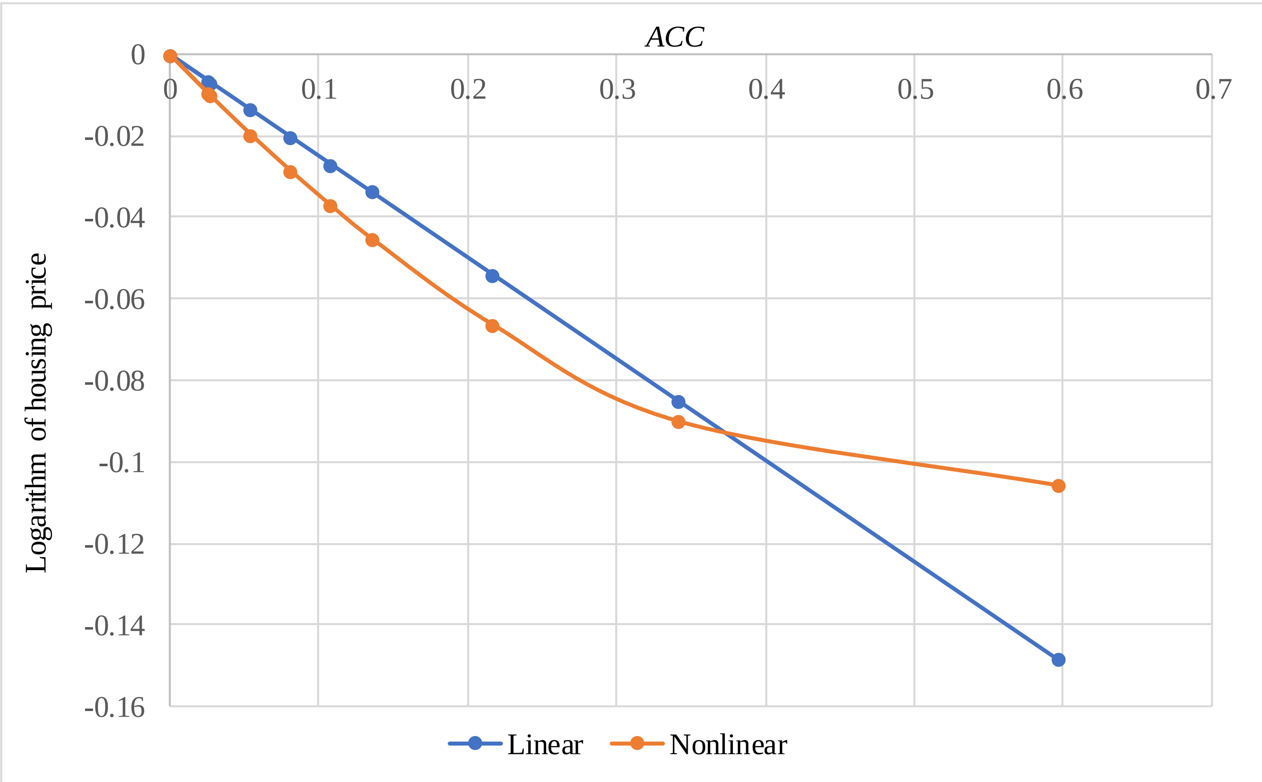

Figure B 2.1 linear and nonlinear relationship between the accessibility of wet market and housing prices

Chapter 3 Economic Valuation of Air Quality Change: Evidence from Housing Market in Beijing, China

This chapter is coauthored by Martijn Smit and Marco Helbich. This paper is currently under review at an international journal.

ABSTRACT

Air pollution is a major environmental urban issue, particularly in fast growing cities in developing countries. Reducing air pollution is thus a challenge, while evaluating the economic value of air quality is a crucial problem in policies to control pollution. However, few studies accurately estimate this value as they neglect the dynamic and heterogeneous effects of air pollution. We therefore assessed the economic effect of particulate matter with a diameter of 2.5 μm ($PM_{2.5}$) on housing prices in Beijing, China. As a proxy for housing prices, we used panel data comprising resale apartment transactions matched with average quarterly pollution data (i.e., $PM_{2.5}$) between 2013 and 2019. We used an instrumental variable approach (IV) to examine the housing price–$PM_{2.5}$ relationship through a hedonic framework. Our results show that households are willing to pay an extra 0.169% per housing unit price for an average quarterly reduction in $PM_{2.5}$ of 1 μg/m^3. The marginal willingness to pay (MWTP) for improved air quality varied across income groups: People with high incomes were willing to pay a premium for clean air than those with low incomes. The MWTP peaked at 432 yuan/m^2 in 2015, and then decreased through policy-based pollution mitigation strategies. Our findings contribute to refining estimates of the economic value of air quality and nuanced understanding the willingness to pay for air quality, which is beneficial for assessing and optimizing valuations of environmental regulations.

Keywords: Hedonic housing prices, Instrumental variables, Willingness to pay, Air quality, Beijing, China

3.1 Introduction

Exposure to air pollution has provoked wide concern as it both threatens human health (Landrigan et al., 2018) and hinders economic development (Dominici et al., 2014; He et al., 2016; Lichter et al., 2017). Considerable efforts have been made to reduce air pollution, especially in fast-growing urban metropolises, such as Beijing. Since air is considered a common good and its pollution is a negative externality to other activities (e.g., labor productivity), it is difficult to judge who should be charged for pollution and what the price should be (Chang et al., 2019; Klingen & Ommeren, 2020; Liu et al., 2020; Schulze et al., 1981). It is therefore important to have accurate estimates of the economic value of air quality as a key input for cost–benefit analyses of cleaner air and pollution regulation strategies for policymakers (Chay & Greenstone, 2005; Freeman III, 1974).

To date, a large body of published research estimate the economic value of air quality improvement with various approaches, such as hedonic technology and avoidance behavior approach (Hitaj et al., 2018; Lebo & Weber, 2015; T. Liu et al., 2018). In which, hedonic price model is in the cost-benefit framework to estimate the benefits of air quality based on its causal impacts on housing prices, which has been adopted prevalently in assessing the value of environmental goods including air quality, noise and other pollutants (Anderson & Crocker, 1971; Baranzini et al., 2010; Zabel & Guignet, 2012). It enable capture the effect of air quality more accurately and objectively in the stable, long-run and dynamic condition, and further calculate residents' marginal willingness to pay (MWTP) to clean air (Bednarz, 1977; Palmquist, 2005), which contributes to making efficient policy-strategy for improving air quality no matter in the long- or short -run.

In this analysis framework of hedonic price model, literature on the effect of air quality on housing prices in developed countries, both across and within cities, is mounting (Bajari et al., 2012; Hitaj et al., 2018; McCord et al., 2018; Kim et al., 2003). For developing countries, although a few studies have compared cities (Chen & Jin, 2019; Freeman et al., 2019; Zou, 2019), the within-city level has been largely neglected and panel studies are lacking (Chen et al., 2018), due to the accessibility of data.

Advancements in industrialization, accompanied with rapid urbanization, has worsened the air quality in most developing countries (Chen et al., 2017; Ebenstein et al., 2015; Greenstone & Hanna, 2014): In 2016, 98% of cities in developing countries did not fulfil the World Health Organization's air quality guidelines (Organization, 2016). Reducing air pollution is therefore among the highest priorities for such areas (Shiva Nagendra et al., 2021). Due to different economic, political, institutional, and cultural settings, it is hardly possible to transfer results from Western to developing countries. Similarly, findings at the inter-urban level are difficult to apply at the finer intra-urban scale because of their differences in backgrounds and drivers of air pollution affecting housing prices (Chen & Jin, 2019; Mei et al., 2020).

To bridge those knowledge gaps, we took Beijing, the capital of China, as a case to detect the influence of air pollution on housing prices by adopting resale transaction data on residential apartments in 2013–19, a period of worsening air pollution across China (Tilt, 2019). We estimated residents' marginal willingness to pay (MWTP) for air quality improvement.

The contributions of our present work to literature are threefold. First, we provide the dynamic preference estimates of local MWTP for clean air at the intra-urban level with average quarterly pollution data. Our use of panel data circumvented bias caused by cross-sectional data and the possible seasonal effect, as well captured the dynamics of the MWTP to avoid air pollution (Hitaj et al., 2018; Hsiao, 2007). Second, our research design allowed us to explore the heterogeneous responses to air pollution for households across different income levels, which are manifested in Beijing's ring road division. Because households with different income levels value air quality differently (Chen et al., 2018; Le Boennec & Salladarré, 2017), our approach also mitigated the risk of an estimation bias. Finally, by adopting an instrumental variable (IV) approach to release the potential endogeneity problem that air pollution is likely to be correlated with unobservable local characteristics, we minimized the estimation bias of the economic value of air quality while examining causal associations (Sullivan, 2016).

3.2 Literature review

3.2.1 Estimation methods for the economic value of air quality

The literature on the economic value of air pollution is mostly concerned with estimating individuals' MWTP for clean air through behavioral changes. Three approaches have been put forward (Baranzini & Ramirez, 2006):

First, the "avoidance/defensive cost" assesses individuals' MWTP by their defensive expenditures for avoiding the consequences of pollution—for example, through wearing face masks or using air purifiers (Ito & Zhang, 2020; Zhang & Mu, 2018). Nevertheless, such behavior is likely to lead to combined influences. Even if avoidance costs are expected to be lower than the costs of possible damages, people would pay to avoid those damages. Thus, using defensive expenditures as a proxy for welfare changes seems problematic when estimating the MWTP for air quality improvement.

Second, the "cognitive preference" adopts contingent valuation methods (CVMs), conjoint analysis surveys, or choice experiments based on individuals' subjective perceptions. For instance, Dong and Zeng (2018) used CVMs to gauge the public MWTP for haze mitigation in Beijing. They found that respondents were willing to pay 0.55–0.82% of their annual income to avoid smog. Strong underlying assumptions are that respondents are familiar with their personal preferences and that people's true willingness to pay is stated objectively and accurately. Since these assumptions are possibly not fulfilled, the willingness to pay for air quality improvement calculated by CVM is possibly biased.

Third, the hedonic pricing approach is frequently applied to determine the economic value of air quality based on its effect on housing prices, in which the non-market goods - air quality could be traded in the housing markets (Freeman, 1981; Palmquist, 2005). In this assumption, residents prefer to live in locations with clean air to minimize the possible health hazards caused by air pollution, as air quality declines but environmental consciousness increases. Housing with greater air quality, on the other hand, has a higher price. As a result, residents make a trade-off between higher housing prices and clean air. Through this technique, real residents' MWTP to air quality improvement could be computed based on the associated coefficient (Adamowicz et al., 1994).

During its' application process, the standard hedonic price model might bring some estimate bias. With cross-sectional data, the endogeneity issue generally is overlooked. With the panel data, the endogeneity, that local economic activities are associated with air quality, and housing prices as well, lower the accuracy of estimates. In addition, there may be heterogeneity effects across income groups. If so, the value of air quality from the average estimates could not give an accurate explanation. In order to overcome these above issues, we estimated the dynamic effect of air quality over time and its heterogeneity effect across income groups, by adopting a novel instrumental variables (IV) approach with panel data.

3.2.2 Housing prices and air pollution under a hedonic pricing approach

Recent studies in developed countries that applied hedonic models reported a negative association between housing prices and air pollutants. For example, at the inter-urban level, Bayer et al. (2009) found the greater MWTP for clean air in US metro regions through the housing market. In terms of the intra-urban level, several studies focused either on US cities or other, mainly European, countries. McCord et al. (2018) used 2013–18 housing sales in the UK to assess the implicit price of air pollution. However, due to contextual differences, it is problematic to transfer Western findings to developing countries (He et al., 2016).

As environmental conditions worsened in many developing countries, studies at an inter-urban level gained momentum. For instance, Chen and Jin (2019) examined inverse air pollution effects on housing prices in China's 286 cities in 2005–13, while Freeman et al. (2019) added regional migration costs to a residential sorting model to more accurately estimate the economic value of air quality in China for 2005. Both studies concluded that Chinese residents are willing to pay extra for clean air. Given that high migration costs do not apply to residents moving within a city, the mechanisms and the willingness to pay to evade air pollution differ between the inter-urban and the intra-urban level.

The few studies that have been done at the intra-urban level were mainly based on cross-sectional data. For instance, using data from Shanghai in 2010, Chen et al. (2018) found adverse effects of air pollution on urban housing prices: Reducing concentrations of sulfur dioxide (SO_2) and PM_{10} by 1 mg/m^3 increased Shanghai's housing prices by, on average, 0.6% and 0.9% respectively (i.e., 159 yuan/m^2 and 238 yuan/m^2). Based on the installation and operation of an air-purifying tower in the city of Xi'an, Lan et al. (2020) adopted a quasi-experimental design—namely a difference-in-difference approach to measure the tower's ability to mitigate haze, and found that it increased housing prices by, on average, 4% across the affected area. He and Collins (2020) and Mei et al. (2020) found negative air pollution effects on housing prices across the metropolises of Guangzhou and Beijing through panel data. However, neither study took into account that dynamic and heterogeneity effects of air pollution with long time series are possible and that results may vary across different population subgroups, likely biasing the estimated economic value of clean air. We addressed these shortcomings in our study.

3.3 Materials and methodologies

3.3.1 Study area

Beijing is China's capital and political center. The incomes and living standards of its 21.54 million residents are higher than those of people in other parts of the country. Because the northern part of China suffers from more severe air pollution than the south (Xu et al., 2019), its residents are likely to care more about their neighborhood environment (Aunan & Wang, 2014). Therefore, Beijing represented an ideal case to explore the economic effect of clean air on housing prices.

Our study focused on the area within Beijing's 6th ring road, as it encompasses the main urban areas (Figure 3.1). The city's ring roads have been designed to relieve central parts from traffic induced through urban sprawl. Beijing's six ring roads, which are centered on Tiananmen Square, enclose mainly residential areas and divide the city into different functional areas (see Table 3.1 in the Appendix) (Gao et al., 2016). The population within the 3rd–6th ring roads accounts for 57% of Beijing's total population (Wang & Bao, 2015). Although a polycentric structure emerges in Beijing (Qin & Han, 2013), housing prices still gradually decline with increasing distance from the inner to the outer ring, which also reflects the spatial difference in residents' income levels (Anas et al., 1998).

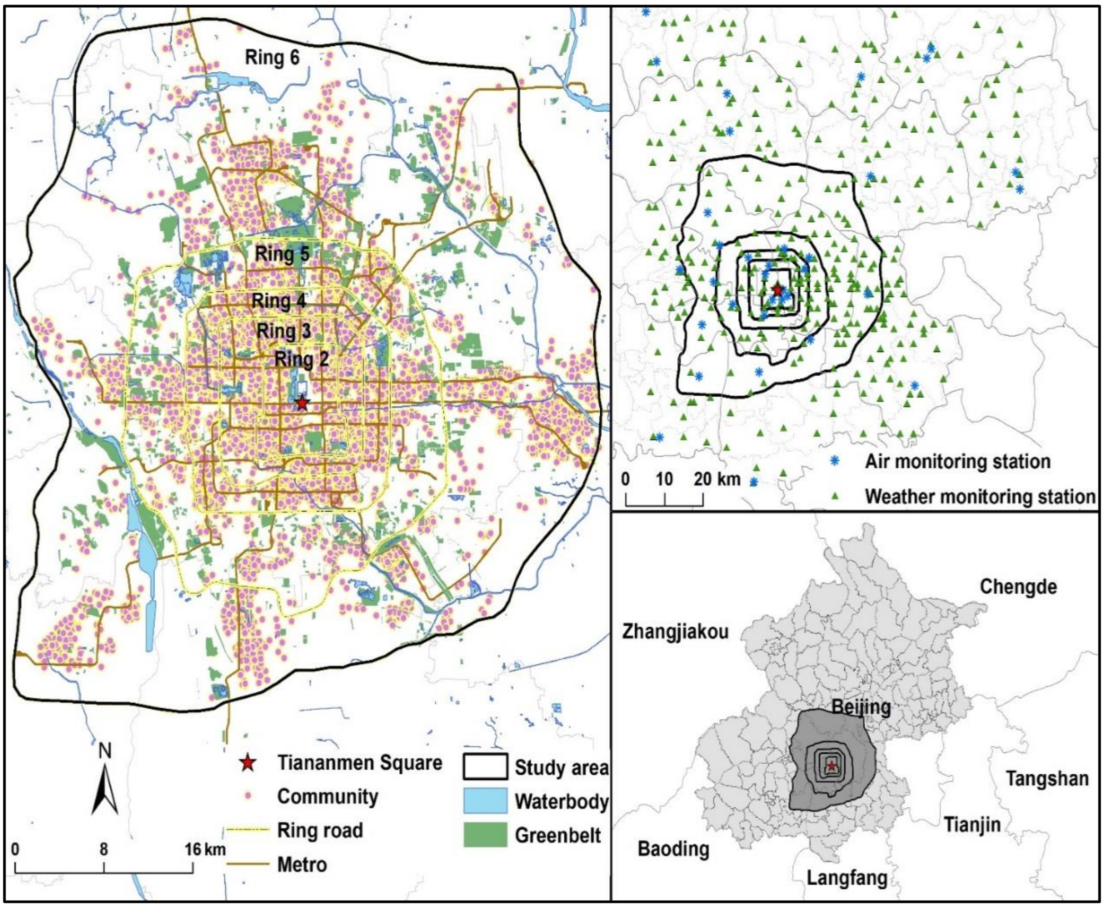

Figure 3.1 The Metropolitan area of Beijing

3.3.2 Data

3.3.2.1 Housing data

Housing transaction data (in units; N=395,040) between 2013 and 2019 on the existing stock was collected through web scraping from the Lianjia[1] platform. The sample excluded public housing programs, and single detached dwellings, and government-subsidized housing. Resale transactions are more likely to reflect true market prices, compared with those of newly built housing units (Li et al., 2019). Per housing unit, we also obtained several structural characteristics (Table 3.1) including, for example, area, floor, orientation, and longitude and latitude.

[1] Lianjia is the largest real estate trading platform in China, covering the sale of new and pre-owned housing sales, and a realtor and housing renovation business. (https://bj.lianjia.com/)

Based on these housing transaction data, we calculated the average prices of each community (i.e., residential quarter or unit consisting of many buildings with housing) and the average quarterly housing price within each ring road over time. We showed the distribution of the average price per community by means of ordinary kriging interpolation (Figure 3.2), which indicates that housing prices roughly decline with increasing distance to the urban centers. Figure 3.3 shows the average quarterly housing prices within each ring road. While the average quarterly housing price increased over time until 2017, a decrease is noticeable thereafter. The price within the inner ring is always higher than within the outer ring, which remains in line with the opinion of Yang and Shen (2008).

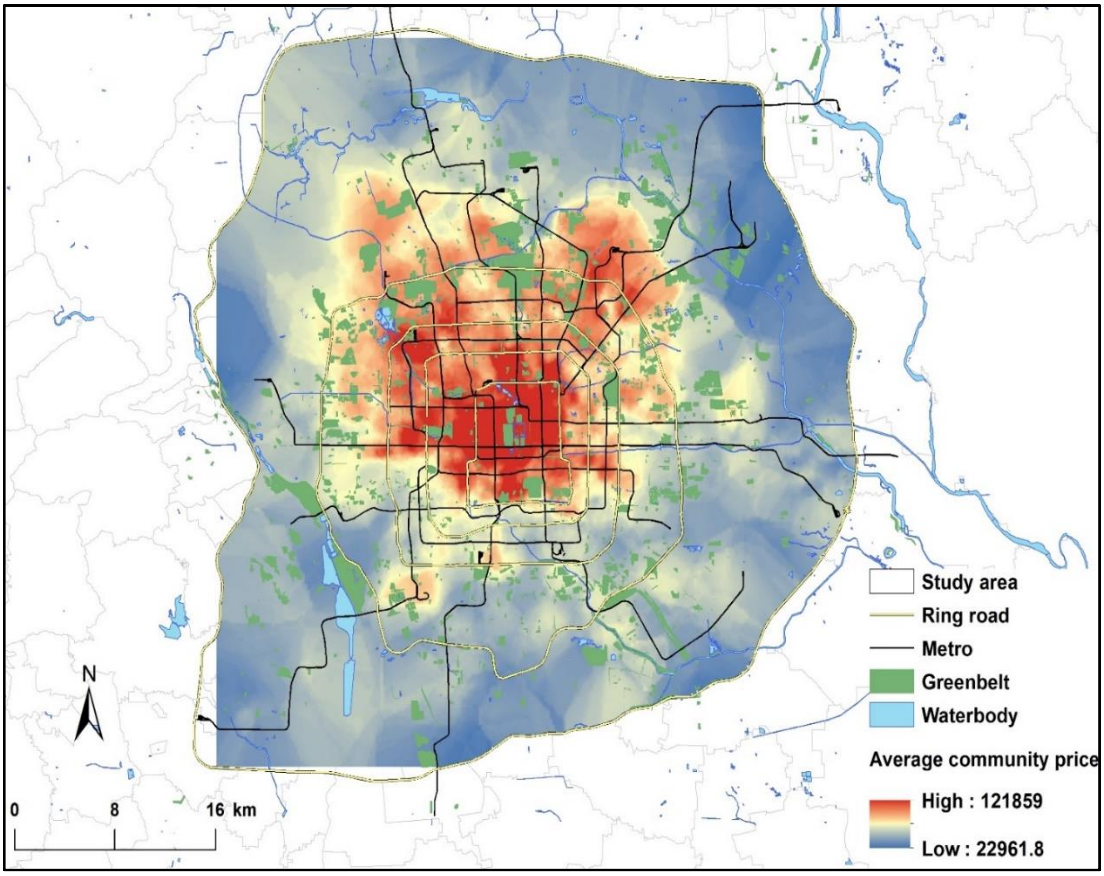

Figure 3.2 Distribution of average community prices based on pooled data

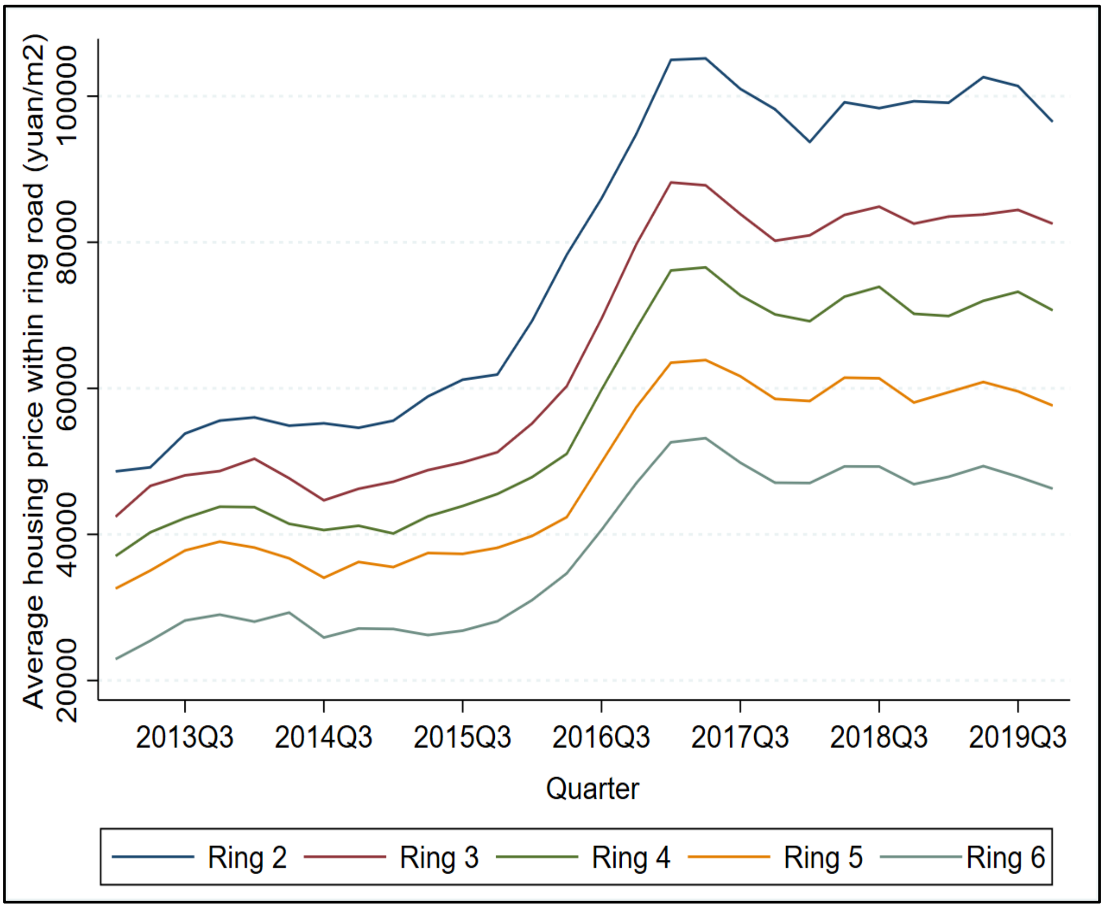

Figure 3.3 Average housing price within each ring road over time

Furthermore, the predicted logarithm of unit price of each community was obtained when we took the logarithm of the unit price per apartment and regressed this price on the control variables, including area, the square of area, floor, orientation, number of bedrooms, decoration, building style, and presence of an elevator. Table 3.2 provides descriptive statistics per variable at housing and community level. After removing observations with missing data, we ended up with 333,269 housing units in 7,051 communities between 2013 and 2019. We then randomly extracted one set of panel data of the 2,794 communities with 33,538 housing units during the 4^{th} quarter of 2013 and the 4^{th} quarter of 2019, in which the time series was relatively complete to reduce the biased influence of data unbalance. The panel data of communities matched with all variables at community level.

3.3.2.2 Neighborhood data

We obtained data on public service amenities (e.g., schools and hospitals) and the population density at the community level (i.e., housing blocks). Amenities for each sample year from 2013 to 2019 were gathered based on the points of interest extracted from Amap (https://www.amap.com/). Their addresses were geocoded with an accuracy of 100%. Population density raster surface with a spatial resolution of 1 km was obtained from WorldPop (https://www.worldpop.org/).

Based on hedonic price theory (Rosen, 1974), besides housing structural attributes, accessibility (i.e., location) and neighborhood quality are key for housing prices. Thus, for each community, we determined the street distance to the nearest city center/subcenter (i.e., Tiananmen Square, Jianguomen central business district (CBD), Beijing Financial Street, the technology hub–Zhongguancun Science Park, and the Olympic Park) (Qin & Han, 2013), and to the nearest school, hospital, city park, shopping mall, farmers' market, bus stops and metro stations, as well as the number of basic services (e.g., post office, laundry) and leisure facilities (e.g., museum, gym) within 1,000 meters[2] per year (Table 3.1).

3.3.2.3 Air pollution and meteorological data

We recorded air pollution data at 35 fixed monitoring stations (Figure 1) as hourly measurements collected from the Beijing Municipal Environmental Monitoring Center (http://www.bjmemc.com.cn/) Meteorological data capturing monthly measurements (i.e., wind speed, precipitation) at 363 fixed weather stations (Figure 1) were gained from China Meteorological Data Service Centre (http://data.cma.cn/).

We calculated quarterly averages of particulate matter with an aerodynamic diameter of <2.5 μm ($PM_{2.5}$). $PM_{2.5}$ is a mixture of solid particles and liquid droplets in the air, which causes smog or hazy conditions. The air pollution in Beijing is caused by not only local emissions (Hefeng Zhang et al., 2016) but also the spillover of pollution from boundary cities, such as Tianjin, Langfang, and Tangshan (Xu et al., 2019) (Figure 1). Reducing $PM_{2.5}$ concentrations is a mandatory target in the "Air Pollution Prevention Action Plan" for the Beijing–Tianjin–Hebei region (Zhang & Wu, 2018). For robustness checks, we also included the quarterly averages of

[2] A distance threshold of 1,000 m was chosen because it corresponds with 15-minutes' walking distance, which is frequently used in community planning.

China's ambient air quality index (AQI) along with $PM_{2.5}$. The AQI is a composite measure comprising six pollutants, namely sulfur dioxide (SO_2), carbon monoxide (CO), nitrogen dioxide (NO_2), PM_{10}, ozone (O_3), and $PM_{2.5}$. We interpolated these variables across the study area on a 20×20 meter grid using ordinary kriging (Anselin & Le Gallo, 2006; Kuntz & Helbich, 2014). Similarly, the quarterly average of meteorological conditions including wind speed and precipitation were interpolated by means of ordinary kriging. Finally, we assigned the estimated concentrations of air pollution and meteorological conditions to each property based on the community within which they are located.

Table 3.1. Description of the variables

Category	Variable	Definition
Housing price	Housing price	Unit price per apartment (yuan/m^2)
Structural attributes	House age	Dummy variable: Age of house divided into decades: Age1 (1950-1979), Age2 (1980-1989), Age3 (1990-1999), Age4 (2000-2009), Age5 (2010-2019)
	Floor area	Floor area (m^2)
	Bedroom number	Number of bedrooms
	Building style	Dummy variable (1=slab-type building; 0=otherwise)
	Orientation	Dummy variable (1=apartments with southern orientation; 0=otherwise)
	Elevator	Dummy variable (1=apartment with an elevator; 0=otherwise)
	Decoration	Dummy variable (Dec1=apartments with refined decoration, Dec2=with simple decoration, Dec3=with roughcast)
	Floor level	Dummy variable (Floor1=top, Floor2=high, Floor3=middle, Floor4=low, Floor5=ground)
Locational accessibility	D_CBD	Distance to the nearest urban center/subcenter (Tiananmen Square, Jianguomen CBD, Beijing Financial Street (BFS), Zhongguancun Science Park (ZSP, the technology hub), Olympic Park) (m)

	D_Bus stop	Distance to the nearest bus stop (m)
	D_Metro sation	Distance to the nearest metro station (m)
Neighborhood characteristics	School	Distance to the nearest school (kindergarten, primary, middle school) (m)
	Hospital	Distance to the nearest hospital (“triple A” and comprehensive hospitals) (m)
	Park	Distance to the nearest city park (m)
	Shopping mall	Distance to the nearest shopping mall (m)
	Famers’ market	Distance to the nearest famers’ market (m)
	Basic services	Number of basic services (e.g., restaurant, barber shop, post office, parcel delivery, laundry) within 1 km
	Leisure facilities	Number of sport and leisure facilities (e.g., karaoke, bar, museum, gym) within 1 km
	Population	Population density per community (people/km^2)
Air pollution	$PM_{2.5}$	Quarterly concentrations of average $PM_{2.5}$ (μg/m^3)
Meteorological conditions	Wind	Quarterly average of wind speed (m/s)
	Precipitation	Quarterly average of precipitation (mm)

Table 3.2.Descriptive statistics

Housing units (N=333,269)

Variable	Mean	Std. dev.	Min.	Max.	Variable	Mean	Std. dev.	Min.	Max.
Housing price	10.82	0.440	1.099	11.92	Age5	0.104	0.305	0	1
Floor area	79.97	34.94	9.640	640	Floor1	0.113	0.316	0	1
Bedroom number	2.000	0.760	0	9	Floor2	0.221	0.415	0	1
Building style	0.264	0.441	0	1	Floor3	0.379	0.485	0	1
Orientation	0.295	0.456	0	1	Floor4	0.204	0.403	0	1
Elevator	1.941	0.739	0	8	Floor5	0.0812	0.273	0	1
Age1	0.615	0.487	0	1	Dec1	0.449	0.497	0	1
Age2	0.148	0.356	0	1	Dec2	0.341	0.474	0	1
Age3	0.279	0.449	0	1	Dec3	0.0197	0.139	0	1
Age4	0.448	0.497	0	1					

Community unit (N= 33,538)

Variable	Mean	Std. dev.	Min.	Max.	Variable	Mean	Std. dev.	Min.	Max.

Community price	0.0291	0.423	-5.104	1.285	Shopping mall	6.953	0.799	0.733	9.278
$PM_{2.5}$	122.396	43.011	47.322	272.47	Farmer's market	6.467	0.983	0.0123	9.031
D_CBD	8.917	0.771	5.869	10.49	Basic services	4.867	1.005	0	6.950
D_Bus stop	6.028	0.921	0.0949	8.689	Leisure facilities	3.984	0.970	0	6.392
D_Metro station	7.066	0.772	0.371	9.418	Population	9.580	0.933	5.418	11.73
School	5.806	1.076	0.0319	8.514	Wind	2.848	1.080	-1.476	4.691
Hospital	6.651	0.874	0.0138	8.867	Precipitation	6.214	1.760	-1.801	9.221
Park	6.742	0.807	0.143	8.872					

3.3.3 Model specifications

3.3.3.1 Model at the housing level

To assemble panel data at the community level, we fitted an ordinary least squares (OLS) regression model at the housing level to estimate the value per community price with fixed quarter and community effects:

$$\ln(HP_{ijt}) = \beta + \alpha S_{ijt} + i.community \times c.quarter + \theta_t + \xi_{ijt} \qquad (1)$$

where $ln(HP_{ijt})$ is the logged transaction unit price of an apartment i in residential community j in quarter t, t belongs to the time range from the 4th quarter of 2013 (2013:Q4) to the 4th quarter of 2019 (2019:Q4). Note that 2017:Q4, 2018:Q3, and 2018:Q4 were excluded due to missing data in these periods. S_{ijt} is a vector of structural features of apartment i in community j and quarter t, α are the coefficients, and ξ_{ijt} is the error term. The regression results with high adjusted R^2 in this stage are shown in Table A 2.2.

3.3.3.2 Benchmark model at the community level

To test the influence of air pollution on housing prices, we first specified a benchmark model (i.e., pooled OLS model) using a semi-log specification at the community level:

$$\ln(CP_j) = \beta + \gamma \ln A_j + \chi \ln N_j + \kappa PM_{2.5j} + \varepsilon_j \qquad (2)$$

where $ln(CP_{ij})$ is the logged price of residential community j, and $A_j, N_j,$ and $PM_{2.5j}$ refer to the accessibility, neighborhood variables, and $PM_{2.5}$ at the community level. β is the constant, γ, χ, and κ are the estimated coefficients, and ε_j is an error term. The non-independence of observations was addressed by means of cluster-robust standard errors with the different communities acting as clusters.

3.3.3.3 Fixed effects model

To eliminate the correlation between the unobserved factors and $PM_{2.5}$ and to obtain an unbiased estimate of the implicit price of air quality, we used the fixed effects (FE) specification based on the Hausman test:

$$FE: \ln(CP_{jt}) = \beta + \gamma \ln A_{jt} + \chi \ln N_{jt} + \kappa PM_{2.5jt} + \sum_t \rho_t \theta_t + \mu_j + \varepsilon_{jt} \qquad (3)$$

where a quarter-fixed effect θ_t controls for time-varying economic shocks (e.g., policy changes in the housing market), and and a community-fixed effect μ_j controls for time-invariant characteristics across communities.

3.3.3.4 Fixed effects two-stage least squares (FE2SLS) model

Endogeneity remains an issue under the FE (or RE) specification if time-varying unobserved factors affect both air pollution and housing prices (Bajari et al., 2012). To ensure more accurate estimates compared to the OLS model, we calculated the relationship between the estimated prices and air pollution by replacing $PM_{2.5}$ with instrumental variables (IV), namely the logarithm of wind speed and that of precipitation. Other studies confirmed that such weather conditions partly reduce air pollutants (Chen & Jin, 2019; Hitaj et al., 2018; Yang & Zhang, 2018). These two IVs satisfy the basic conditions, namely instrument relevance (i.e., corr $(Z, X) \neq 0$) and instrument exogeneity (i.e., corr $(Z, \varepsilon) = 0$), where X is the endogenous variable $PM_{2.5}$ and ε is the random perturbed variable. Our first-stage equation is:

$$PM_{2.5jt} = \beta + v_1 \ln wind_{jt} + v_2 \ln Precipitation_{jt} + \gamma \ln A'_{jt} + \chi \ln N'_{jt} + \sum_t \rho_t \theta_t + \mu_j + \varepsilon_{jt} \qquad (4)$$

and the second-stage equation is:

$$\ln(CP_{jt}) = v + \gamma \ln A''_{jt} + \chi \ln N''_{jt} + k\widehat{PM_{2.5jt}} + \sum_t \rho_t \theta_t + \mu_j + w_{jt} \qquad (5)$$

where $\widehat{\mathrm{PM}_{2.5jt}}$ is the predicted ambient $PM_{2.5}$ concentration in community j in quarter t. The other variables and coefficients are similar to those in Eq. (3).

3.3.3.5 Dynamic effects

To assess whether and, if so, how residents' awareness of and MWTP for air quality improvement change over time, we further explored the dynamic effects of air pollution on housing prices by adding $PM_{2.5}$ × year interaction terms:

$$\ln(CP_{ijt}) = \beta + \gamma \ln A_{jt} + \chi \ln N_{jt} + k_0 PM_{2.5jt} + k_y (PM_{2.5jt} \times Year_y) + \sum_t \rho_t \theta_t + \mu_j + \varepsilon_{ijt} \qquad (6)$$

where the year 2013 is set as the base period, and the dummy variable *Year* means 1 in the *y* year and 0 otherwise, comprising 2014 to 2019. The estimate coefficient k_y captures the changing difference in the effect of air pollution on housing prices compared with the base period 2013.

3.4 Results and discussion

3.4.1 Basic regression results

Table 3.3 reports the results of pooled OLS, Two-way FE[3], and FE2SLS regressions. Given that the variance inflation factors (VIF) of the independent variables reached a maximum of 1.09—which is far below the critical value of 10—multicollinearity was not an issue in our models. The estimated coefficients for $PM_{2.5}$ were, as expected, negative and significant at least at the 5% level, showing that pronounced $PM_{2.5}$ levels are likely to reduce housing prices. The FE model resulted in much smaller effect sizes than the OLS did; however, the OLS model tends to overestimate because it neglects endogeneity.

In the IV regression, the results of the *F*-statistic exceeded 10 in the first stage, indicating that the IVs were suitably correlated with the endogenous variable. The Sargan statistic was insignificant (p=0.777), indicating overidentifying for the IVs. The IV estimates were considerably higher than the FE estimates but smaller than that of OLS. The effect of $PM_{2.5}$ according to the IV estimation was more reasonable, implying that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration causes a 0.169% reduction in the housing unit price. This decrease was smaller compared with findings reported for other major Chinese cities, including Shanghai (0.9% for PM_{10}) (Chen et al., 2018).

Some estimates for the control variables, including accessibility and the neighborhood characteristics, were significant in the OLS but not in FE and FE2SLS models; their signs were, however, in line with expectations and largely consistent with earlier studies (Qin & Han, 2013;

[3] The Hausman test was significant (p=0.00), indicating that the FE model fits better than the RE model.

Yuan et al., 2018). Since the distance to the nearest urban center/subcenter for each community point does not change over time, coefficients for D_CBD were not estimated in the FE and FE2SL models. Based on the FE2SL results, except for distance to the nearest bus stop, none of the additional control variables displayed a statistically significant marginal covariation with housing prices during the period of study. This may be by reason of correlations with the estimated prices at community level or other confounding factors.

Table 3.3 Regression results

	(1)	(2)	(3)
	OLS	FE	FE2SL
$PM_{2.5}$	-0.00759***	-0.000459***	-0.00169**
	(0.000185)	(0.0000663)	(0.000710)
School	0.000588	-0.000692	-0.000837
	(0.00147)	(0.000543)	(0.000552)
Hospital	0.00229	0.000102	-0.0000492
	(0.00187)	(0.00130)	(0.00131)
Park	-0.00190	-0.000828	-0.000901
	(0.00200)	(0.00112)	(0.00113)
Shopping mall	0.00351	-0.00118	-0.00134
	(0.00228)	(0.00102)	(0.00103)
Farmer's market	0.000348	0.000237	0.000247
	(0.00179)	(0.000721)	(0.000726)
Leisure facilities	0.0116***	-0.00133*	-0.00111
	(0.00188)	(0.000709)	(0.000725)
Basic services	0.00540***	0.000541	0.000607
	(0.00177)	(0.000640)	(0.000645)

Population	0.176***	-0.00340	-0.00368
	(0.00184)	(0.00384)	(0.00387)
D_Bus stop	0.00103	-0.00208**	-0.00224**
	(0.00189)	(0.000943)	(0.000954)
D_Metro station	0.00105	0.000599	0.000835
	(0.00226)	(0.00200)	(0.00202)
D_CBD	-0.0150***	0	0
	(0.00233)	(.)	(.)
Constant	-0.405***	-0.105**	0.388***
	(0.0566)	(0.0444)	(0.0718)
Quarter fixed effects	Yes	Yes	Yes
Community fixed effects	Yes	Yes	Yes
N	33538	33538	33538
Adjusted R^2	0.490	0.877	0.874

Heteroskedasticity-robust standard errors clustered at the community level. Standard errors in parentheses. Significance levels: $p<0.1$, $p<0.05$, $p<0.01$.

3.4.2 Robustness check

To evaluate the robustness of our result for $PM_{2.5}$, we re-estimated the OLS, FE, and FE2SL models with the AQI as an alternative proxy for air pollution. Again, the coefficients were negative and statistically significant (Table A 3.3 in the Appendix). Except for the OLS model, the AQI coefficients were slightly smaller than those for $PM_{2.5}$, but their signs and magnitudes were in keeping with those of $PM_{2.5}$ in corresponding models. These results imply that our estimates for $PM_{2.5}$ were robust.

3.4.3 Heterogeneous effects of $PM_{2.5}$

The ring roads of Beijing correspond to areas with different income levels. The average housing price within the inner ring is higher than within the outer rings, and the city shows an overall urban structure with a price decay toward the countryside (Dai et al., 2016). Therefore, to assess variation across income groups, we ran stratified analyses based on ring roads 2–6. Figure 3.4 shows the estimation results for $PM_{2.5}$ using FE2SLS regressions (Table A 3.4 in the Appendix). The overall adjusted R^2 decreased somewhat as we moved from the inner toward the outer rings, but increased slightly for the ring 6 regression. The Chow test statistic showed that the coefficients of $PM_{2.5}$ within each ring road are significantly different. The significant negative $PM_{2.5}$ estimates for all rings confirm the negative influence of $PM_{2.5}$ on housing prices in our city-wide model, except that the result for ring 4 seems counterintuitive. However, the magnitude of the estimates gradually decreased with increasing distance from the core city, that is, a 1 $\mu g/m^3$ increase in $PM_{2.5}$ leads to an average reduction in the housing price of 0.358% and 0.0958% within rings 2–3, and 0.153% and 0.14% within rings 5–6. Thus, the negative effects of $PM_{2.5}$ within the inner rings were larger than those within the outer ones. In contrast, the negative influence of $PM_{2.5}$ within rings 5–6 slightly increased; it is possible that the most suburban districts within rings 5–6 attract more wealthy households, who are willing to pay extra for a healthier living environment (Chen et al., 2018; Hu et al., 2014b).

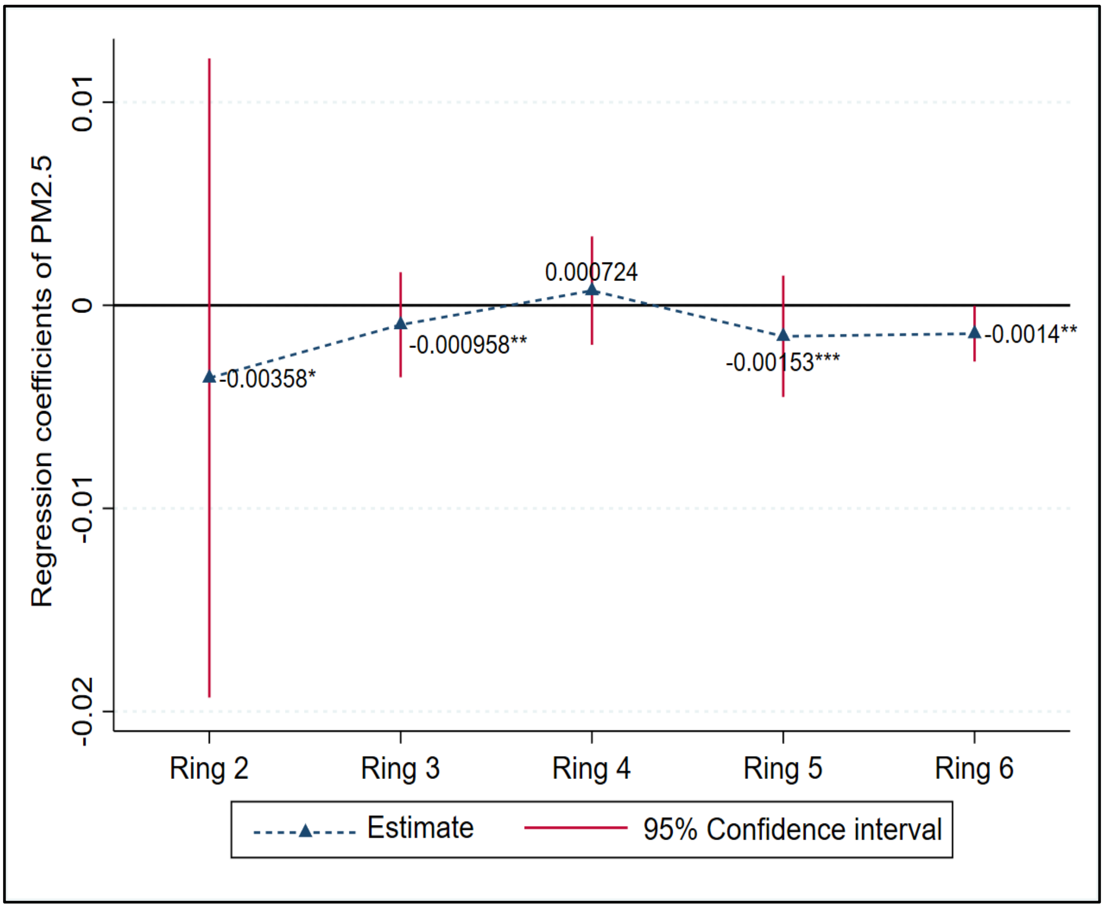

Figure 3.4 Regression coefficients of $PM_{2.5}$ within each ring road

3.4.4 Dynamic effects

Taking 2013 as baseline, Figure 3.5 shows the difference concerning the estimated $PM_{2.5}$ effect between 2014 and 2019 compared with 2013. The coefficient for 2013 was -0.00346 and statistically significant at the 1% level. Compared with 2013, the estimated coefficient decreased to -0.00201 in 2014 and to -0.00696 in 2015, indicating that the negative effect of $PM_{2.5}$ intensified over time. However, the $PM_{2.5}$ effects in 2016 and 2018 were not significantly different from the effect in 2013. In 2017, the $PM_{2.5}$ effect was less negative than in 2013, with a different estimate (0.00254) at the 1% level. In 2019, the estimated $PM_{2.5}$ decreased to 0.00176 relative to 2013, but the decrease is less than in 2014 and 2015. Our results suggest that $PM_{2.5}$ had a stronger influence on housing prices after the severe smog in 2013 (Mei et al., 2020), but that recently the effect has weakened to a minor extent. This may be due to air quality improvements across Beijing over time as a result of various environmental policies, such as the Clean Air Action Plan 2013–2017 (Hefeng Zhang et al., 2016).

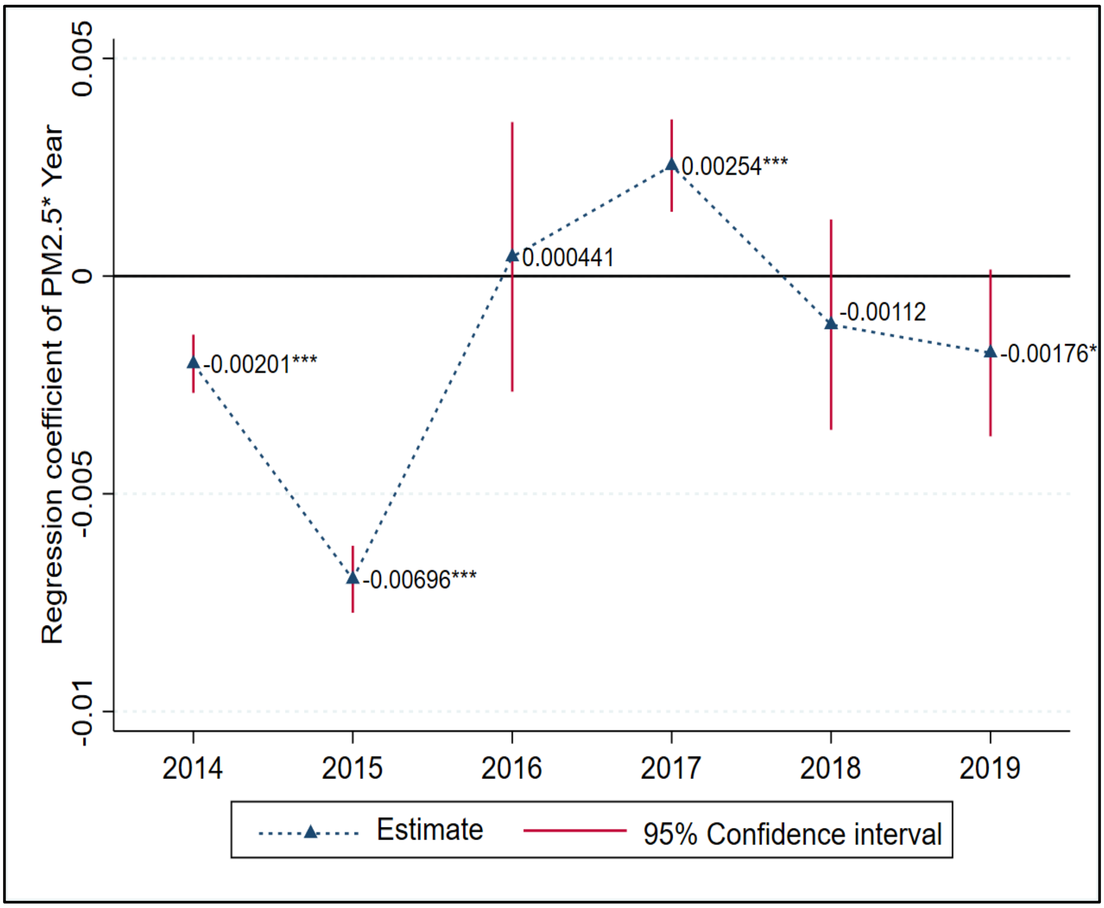

Figure 3.5 Changes in $PM_{2.5}$ estimates compared to 2013

3.4.5 Households' MWTP for air quality improvement

The hedonic framework suggested that households are willing to pay for clean air in order to improve their health and happiness (Rosen, 1974). Thus, the individual MWTP for air quality improvement can be estimated by property values (Freeman III, 1974). The marginal implicit price of air quality refers to the increase in expenditure on a housing unit to one unit of air quality. When a household is in equilibrium, the marginal implicit price of air quality equals the corresponding MWTP for improvements in air quality.

The MWTP was calculated at the community unit price le vel[4], which we interpreted as representing household MWTP. The household's willingness to pay was determined by the change in the annual average per-unit pre-owned housing price. The MWTP from the FE2SLS

[4] We regarded the average unit price of the existing housing stock to be the same as the community unit price, thus disregarding newly built homes.

model was the largest. On average, households are willing to pay each quarter 0.169% of their mean per housing unit price for a 1 μg/m^3 reduction in $PM_{2.5}$ (-0.00169, Table 3.4 column 4). The average payout rate was lower than in earlier cross-sectional studies for Qingdao (Chen & Chen, 2012) and Shanghai (Chen et al., 2018), or an annual study for Beijing (Mei et al., 2020). This difference is probably related to our stronger analysis design (i.e., cross-sectional vs. panel data, annual vs. quarterly panel data), but could also be attributed to environmental improvements in Beijing.

Using the coefficients from FE2SLS the regressions for separate years, we calculated the household's MWTP for $PM_{2.5}$ improvements from 2013 to 2019 based on the current housing price (Table 3.4). The household's MWTP of 2013 and 2014 for a reduction in 1 μg/m^3 $PM_{2.5}$ was 140 yuan/m^2 and 204 yuan/m^2, respectively, which is comparable with the 159 yuan/m^2 estimated for SO_2 (Chen et al., 2018). The MWTP reached the maximum of 432 yuan/m^2 in 2015 and then dropped sharply to 199 yuan/m^2 in 2016 and to 53 yuan/m^2 in 2017. This decline coincided with a decrease in the mean concentration of $PM_{2.5}$ in 2016 and 2017. In 2017, the concentration was <60 μg/m^3 and met the targets outlined in Beijing's Clean Air Action Plan 2013–2017. However, the MWTP increased from 207 yuan/m^2 in 2018 to 306 yuan/m^2 in 2019, which may be related to changes in peoples' environmental perception.

Table 3.4 Household's marginal willingness to pay (MWTP) per housing unit price for air quality

Year	Estimated coefficient of $PM_{2.5}$ in each year	Average annual m^2 price for pre-owned housing unit in Beijing (yuan/m^2)[5]	MWTP for a reduction of 1 μg/m^3 (yuan/m^2)
2013	-0.00346	40342	139.583
2014	-0.00547	37294	203.998
2015	-0.01042	41494	432.367

[5] Annual average housing unit prices in Beijing were obtained from Anjuke.com (https://www.anjuke.com/fangjia/)

2016	-0.00346	57597	199.285
2017	-0.00092	57768	53.147
2018	-0.00346	59868	207.143
2019	-0.00522	58568	305.725

Note: (100 Yuan = 12.72 EUR= 14.84 USD)

3.5 Conclusions

We valued the economic effect of $PM_{2.5}$ on housing prices by using the resale transaction data of residential apartments in Beijing from 2013 to 2019, and how the $PM_{2.5}$ effects vary across urban strata and over time. In keeping with most previous studies in both developed and developing countries (Chasco & Le Gallo, 2015; Hitaj et al., 2018; Tian et al., 2017), our results showed that $PM_{2.5}$ is negatively associated with housing prices. Moreover, we found that households are willing to pay 0.169% of the housing unit price for a reduction of 1 μg/m^3 in $PM_{2.5}$ concentrations. This result indicates that the MWTP in Beijing is relatively moderate compared to that in developed countries (e.g., the USA) (Bajari et al., 2012), and in other major Chinese cities (e.g., Shanghai, Qingdao) (Chen et al., 2018; Chen & Chen, 2012).

Spatially stratified models showed that the negative influence of $PM_{2.5}$ within Beijing's inner ring roads is larger than within the outer rings. We found that the MWTP for less $PM_{2.5}$ varied across different areas, which we associate with different income groups. High-income households are willing to pay more for clean air than are low-income groups, echoing the results of prior studies (Chen et al., 2018). It seems that the rich care more about the health risks attributed to air pollution and thus tend to pay extra for good air quality, while monetary costs prevent the poor from this amenity, since they have to spend their money on fixed costs and living essentials (Dong & Zeng, 2018). Based on our findings, it seems reasonable to tax high-income households to a larger degree when air pollution funds are set up.

Finally, we examined whether the $PM_{2.5}$ effect varies temporally relative to the year 2013. We found that the negative impact gradually increased in 2014 and 2015. This could mean that the public became increasingly aware of health-threatening impacts owing to exposure to air pollutants in 2013. However, the effect in 2016 and 2018 is not significantly different from that in 2013. Given the decrease in 2017 and the slight increase in 2019, on the whole the negative effect mainly declined. This decline may be associated with pollution control actions like the Clean Air Action Plan 2013–2017. In fact, the measured concentration levels of $PM_{2.5}$ in 2017 and 2019 met the targets of that action plan (Zhang et al., 2016). Hence, the dynamic effects also implicitly provide evidence for the effectiveness of Beijing's environmental regulation actions. Further research is needed to determine whether it is the current reduction in pollution or future government commitments to improve air quality that impact the current willingness to pay.

Our study had several limitations that must be considered when interpreting our findings. First, we incorporated only average quarterly $PM_{2.5}$ concentrations as a proxy for air pollution rather than daily measurements. Though indirectly considered in our sensitivity tests with the AQI, we cannot exclude those other pollutants (e.g., SO_2, NO_2, PM_{10}) may affect housing prices differently. More pollutants indicators should be considered in future work. Second, air pollutant data stemmed from a restricted number of official monitoring stations that are unevenly distributed across space. While our air pollution data facilitated the incorporation of spatiotemporal trends in $PM_{2.5}$, small-scale variations are likely to have been unrecognized. Whether and, if so, to what extent this limitation affected our estimates needs to be addressed in the future using high-resolution air pollution data. Finally, because we used a hedonic model specification, we only indirectly evaluated the willingness to pay for clean air based on the housing market conditions, without obtaining people's perceptions directly. Future research is advised to combine subjective and objective measures to comprehensively explore the effect of air pollution.

3.6 Appendix

Table A 3.1 Overview of areas within each of Beijing's ring roads

Ring road	Construction period	Areas connected	Functions of the area inside each ring
Ring #1	1920s–1950s	Boundary does not exist anymore; Tiananmen, Forbidden City, and Di'an men	Historical areas
Ring #2	1980s–1990s	Dongcheng Qu (Eastern Urban Precinct), Xicheng Qu (Western Urban Precinct), Xuanwu Precinct and Chongwen Precinct	Old city
Ring #3	1980s–1990s	Beijing's CBD (Guandongdian) and diplomatic communities (Dongzhimenwai / Liangmaqiao, Jianguomenwai)	Central business district (CBD), as well as an important residential area for the local population
Ring #4	Completed in 2001	Connects the Zhongguancun technology hub, western Beijing, the Fengtai District, and eastern Beijing	Economic development zones, but also an important residential area for the local population
Ring #5	Completed in 2003	Located approximately 10 km from central Beijing, and links the suburban areas of Huantie, Shigezhuang, Dingfuzhuang, etc. Also passes through the Beijing Development Area.	Residential area for immigrant population
Ring #6	2001–09	Shunyi District, Tongzhou District, Changping District, and Daxing District	Suburban districts

Table A 3.2 Regression results of housing prices in the first stage

Variables	Coefficients	Variables	Coefficients
Floor area	-0.00179***	Floor1	-0.0324***
	(0.0000294)		(0.00853)
Age1	#	Floor2	0.00618
	#		(0.00849)
Age2	0.0431***	Floor3	0.0110
	(0.00245)		(0.00849)
Age3	0.0492***	Floor4	0.00149
	(0.00269)		(0.00852)
Age4	0.0631***	Floor5	0.0131
	(0.00306)		(0.00861)
Age2	0.0336***	Bedroom number	0.0207***
	(0.00445)		(0.000884)
Elevator	-0.0210***	Orientation	0.0220***
	(0.00132)		(0.000616)
Dec1	0.0214***	Constant	10.86***
	(0.00112)		(0.00897)
Dec2	-0.00185		
	(0.00113)		
Dec3	-0.0157***		
	(0.00185)		
Quarter fixed effects	Yes		
Community fixed effects	Yes		
N	333269		
Adjusted R^2	0.925		

Heteroskedasticity-robust standard errors clustered at community level, and standard errors in parentheses. (* p<0.1, ** p<0.05, *** p<0.01).

Table A 3.3 Robustness check for air quality: Regression estimates for AQI

	(1)	(2)	(3)
	OLS	FE	FE2SLS
AQI	-0.00769***	-0.000157*	-0.00113*
	(0.000258)	(0.0000826)	(0.000951)
School	0.000849	-0.000628	-0.000731
	(0.00148)	(0.000543)	(0.000549)
Hospital	0.00286	0.000166	0.000149
	(0.00189)	(0.00130)	(0.00132)
Park	-0.00179	-0.000814	-0.000804
	(0.00203)	(0.00112)	(0.00113)
Shopping mall	0.00268	-0.00111	-0.00129
	(0.00230)	(0.00102)	(0.00104)
Farmer's market	-0.000147	0.000239	0.000184
	(0.00182)	(0.000722)	(0.000727)
Leisure facilities	0.0107***	-0.00142**	-0.00136*
	(0.00190)	(0.000709)	(0.000716)
Basic services	0.00479***	0.000501	0.000608
	(0.00181)	(0.000640)	(0.000650)
Population	0.182***	-0.00325	-0.00331
	(0.00187)	(0.00384)	(0.00386)
D_Bus stop	0.00120	-0.00200**	-0.00222**
	(0.00191)	(0.000944)	(0.000957)
D_Metro station	0.000667	0.000505	0.000349
	(0.00231)	(0.00200)	(0.00202)

D_CBD	-0.0147***	0	0
	(0.00235)	(.)	-0.00113
Constant	-0.657***	-0.224***	0.392***
	(0.0618)	(0.0447)	(0.124)
Quarter fixed effects	Yes	Yes	Yes
Community fixed effects	Yes	Yes	Yes
N	33538	33538	33538
Adjusted R^2	0.481	0.877	0.873

Heteroskedasticity-robust standard errors clustered at community level, and standard errors in parentheses. (* p<0.1, ** p<0.05, *** p<0.01).

Table A 3.4 Heterogeneous effects: estimators based on the ring road (FE2SLS)

	(1)	(2)	(3)	(4)	(5)
	Ring 2	Ring 3	Ring 4	Ring 5	Ring 6
$PM_{2.5}$	-0.00358*	-0.000958**	0.000724	-0.00153***	-0.00140**
	(0.00803)	(0.00132)	(0.00136)	(0.00152)	(0.000700)
School	-0.00113	-0.00246**	-0.000185	-0.000604	-0.000114
	(0.00169)	(0.00106)	(0.00108)	(0.00151)	(0.000954)
Hospital	0.000254	-0.000903	-0.000763	0.00196	-0.00159
	(0.00471)	(0.00248)	(0.00260)	(0.00343)	(0.00237)
Park	0.0000361	-0.00117	-0.00159	-0.00378	0.0000656
	(0.00320)	(0.00194)	(0.00248)	(0.00321)	(0.00192)
Shopping mall	0.00137	0.00196	-0.00110	-0.00130	-0.00384**
	(0.00291)	(0.00184)	(0.00206)	(0.00291)	(0.00184)
Farmer's market	0.00115	-0.000329	0.000206	-0.00108	0.000562

	(0.00205)	(0.00131)	(0.00155)	(0.00184)	(0.00129)
Leisure facilities	-0.00577**	-0.000860	-0.00265*	0.000645	-0.00201
	(0.00288)	(0.00135)	(0.00150)	(0.00187)	(0.00124)
Basic services	-0.00115	0.000120	0.00269*	0.000436	0.000488
	(0.00202)	(0.00108)	(0.00148)	(0.00176)	(0.00110)
Population	-0.0161	0.00139	-0.00772	-0.00175	-0.00634
	(0.0188)	(0.00814)	(0.0120)	(0.0119)	(0.00482)
D_Bus stop	0.00210	-0.00369**	-0.00295	0.00325	-0.00173
	(0.00244)	(0.00184)	(0.00187)	(0.00298)	(0.00167)
D_Metro station	-0.0136	0.00638*	0.00219	-0.00553	-0.00251
	(0.00901)	(0.00333)	(0.00367)	(0.00687)	(0.00357)
D_CBD	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Constant	1.218	0.507***	0.336**	0.291*	0.121
	(0.790)	(0.139)	(0.168)	(0.162)	(0.0838)
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Community fixed effects	Yes	Yes	Yes	Yes	Yes
N	2158	7189	7928	6369	9878
Adjusted R^2	0.943	0.917	0.868	0.818	0.894

Heteroskedasticity-robust standard errors clustered at the community level. Standard errors in parentheses. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Chapter 4 Urban Housing Prices and Regional Integration: A Spatial Analysis in the City of Kaifeng, China

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ABSTRACT

Regional integration is increasingly used as a policy strategy to accelerate urban development and regional cooperation. The present research assessed the effects of regional integration on housing prices to evaluate policy effectiveness for small and medium-sized cities on the peripheries of core cities. Taking as a case study the Chinese city of Kaifeng—a contiguous city in the Zhengzhou megaregion—we utilized hedonic house price modelling and spatial econometrics to investigate the effect of Kaifeng's integration with the core city on the dynamics and determinants of housing prices between 2001 and 2016. The results show that housing prices in Kaifeng increased significantly after the city's integration with Kaifeng in 2005. Further, the results confirm that the regional integration had a significantly positive effect on housing prices, especially in border areas. Moreover, the new time-saving cross-border light rail system had more influence on the prices of nearby housing than the new expressway, and new urban districts with high-quality amenities led to a sharp rise in housing prices in Kaifeng. Our findings offer policymakers some guidance concerning regional cooperation and urban development.

Keywords: Regional integration; Urban housing prices; Urban development; Kaifeng, China

4.1 Introduction

Government policies and planning have a substantial impact on the housing market (Hui & Wang, 2014; Qin & Han, 2013; Zhou, 2018). Numerous studies have examined how housing prices are affected by government interventions, including mortgage policies (Gimeno & Martinez-Carrascal, 2010; Iacoviello & Neri, 2010), sale price restrictions, purchase restrictions (Li & Xu, 2016; Li et al., 2017), land-use regulations, and land supply policies (Ihlanfeldt, 2007). While these studies have broadened our knowledge of the effects of policies on both long- and short-term housing market dynamics at the inter-urban scale (Li & Xu, 2016; Li et al., 2017; Roh & Wu, 2016), research exploring the influence of government policies at the inner-city level is limited.

Urban development policies are increasingly debated in housing literature, as they are thought to influence the locational and neighborhood characteristics of properties, and thus also property prices (Boarnet & Chalermpong, 2001). This is supported by studies on housing renewal (Liu, 2010), urban amenities (Yuan et al., 2018), urban street configuration (Xiao et al., 2014), polycentric urban restructuring (Qin & Han, 2013), urban regeneration (Faye & Fur, 2012) , and new town construction (Firman, 2004). To date, such studies in the Chinese context have been limited to a few megacities, for example, Beijing, Shanghai, Hangzhou, and Nanjing (Feng & Lu, 2013; Wen et al., 2015; Xu et al., 2015; Yuan et al., 2018). The present research extended the analyses to small and medium-sized cities, which we hypothesized differ from metropolises regarding the influence mechanism.

In recent years, regional integration has become the Chinese government's national strategy for achieving "new-type urbanization"[1] (Chen et al., 2018). Such integration facilitates the exchange of labor and capital, the sharing of public resources, and a reduction in transportation costs. It also promotes cooperation among contiguous cities (Chen et al., 2018; Fang & Yu, 2017), which further enhances inter-urban socioeconomic interaction and accelerates inter-urban

[1] "New-type urbanization" stresses the development of urban culture and public services by means of people-oriented urbanization, and facilitates regional integration by eliminating administrative barriers across regions to promote coordinated regional development.

population migration (Feng, 2003; Vickerman, 2015; Zheng & Wan, 2014), and improves the quality of life in underdeveloped areas (Zheng & Wan, 2014). Evidence, albeit weak, suggests that regional integration policies are beneficial for cross-border urban developments and population agglomeration, which coucld lead to higher housing prices close to the border region (Fujimura, 2004; Vickerman, 2015). Unlike the spatial distribution of housing prices in monocentric or polycentric urban areas, the spatiotemporal dynamics of urban housing prices during regional integration are regarded as the central indicator of the efficiency of regional integration policies (Gong et al., 2015; Gong et al., 2016; Song & Liu, 2018).

Taking the city of Kaifeng in the province of Henan, China, as our case study, we assessed the effect of regional integration on housing prices in a city on the periphery of a core city given the process of regional integration. Kaifeng was integrated with the capital city of Zhengzhou (Zheng & Kai Integration; ZKI) between 2005 and 2016. Hence, Kaifeng presented an ideal opportunity to assess the effects of regional integration on housing prices. The two research questions were:

(1) How did housing prices change in Kaifeng in the context of the ZKI?

(2) How did the integration policies affect urban housing prices in Kaifeng at different stages of integration?

4.2 Literature review

4.2.1 Urban development and housing prices

It is well known that urban development is closely associated with housing prices (Baumont, 2004, 2010), and that the implicit prices of housing attributes, especially neighborhood and locational characteristics, are affected by different urban development policies (Baumont, 2007; Kauko, 2009). First, the quality and distribution of urban amenities play a central role in explaining housing price variation. Along with economic growth and improvements in the standard of living in China, residents increasingly prefer urban amenities (Huang & Yin, 2014; Lu et al., 2013). Access to public facilities such as schools, hospitals, and public transportation makes people's daily lives easier, which can be capitalized into housing prices (Hui et al., 2012). The quality and accessibility of these facilities to a great extent determine residents' locational choices and strongly affect housing prices (Wen et al., 2017; Yuan et al., 2018). Likewise, despite not having tangible market prices, urban green landscapes and historical amenities—such as parks, lakes, seascapes, and wetlands—provide leisure opportunities and aesthetic enjoyment to enrich urban life, the values of which thus are reflected in the prices of nearby housing (Hui et al., 2012; Zahirovic-Herbert & Chatterjee, 2012).

Second, urban planning indirectly influences housing prices through the layout of urban infrastructure and public amenities. Urban planning is one measure taken in response to rapid urbanization and the urban cycle (Lu et al., 2013), where housing prices are sensitive to specific projects such as new zone construction or urban regeneration (Baumont, 2007; Wen & Tao, 2015). New town building is generally defined as the construction of a new urban center that creates new opportunities for employment and economic growth, and has higher quality buildings and public amenities compared with other areas (Cho & Kim, 2017), which contributes to a housing price premium and attracts new residents. Housing prices also increase with the updated neighborhood environment created by urban regeneration projects, which are intended to improve the quality of life by refurbishing old buildings and creating amenities in deprived areas (Faye & Fur, 2012; Leather & Nevin, 2014; Lee et al., 2017).

Finally, housing price variation is also affected by the urban spatial structure (Wen & Tao, 2015). Along with the process of urban sprawl, housing and employment have become more decentralized, and there has been a shift in urban spatial configuration from monocentric to polycentric (Maldonado et al., 2013; Helbich, 2015). In the monocentric model, both employment and amenity centers are clustered in the traditional central business district (CBD), to and from which residents need to commute. The monocentric distance–decay function demonstrates a trade-off between commuting cost and housing prices (Alonso, 1964). As the polycentric model emerges, the specialization of subcenters and the decentralization of economic activities broaden the scope of housing location choice (McDonald & McMillen, 1990), and the premium of CBD accessibility shifts to the accessibility of different subcenters. Some empirical research has found that multiple subcenters have a stronger influence than the urban CBD on the housing price distribution (Dubin & Sung, 1987; Wen & Tao, 2015) and that the transportation infrastructure has a stronger impact on the spatial change in housing prices (Qin & Han, 2013).

4.2.2 Regional integration and housing prices

Due to rapid urbanization and intensive urban competition, regional integration is now shaping regional spatial patterns in China and strengthening both the exchange of labor, capital, and knowledge, and the network connections between cities (Chen et al., 2018; Fang & Yu, 2017). Regional integration is embodied in city integration, metropolitan region, and urban agglomeration at the inter-urban scale; examples are the Yangtze Delta urban agglomeration, the Central Plain urban agglomeration, and the Nanjing city-region (Gao et al., 2017; Luo & Shen, 2009). Integrated regions are usually identified by means of population density, urban functions, and spatial continuity. Urban agglomeration and metropolitan regions require hierarchical structures with large, medium-sized, and small cities (Fang & Yu, 2017), while city-regions cover different spatial organization patterns, including a core city and its neighboring cities, without limiting the structure and scales (Fang & Zhang, 2014). Thus, regional integration not only affects the supply of and demand for housing, but also acts on spatial changes in housing prices as described through the hedonic model. Regional integration affects the housing market in several ways.

First, it accelerates regional economic growth, but its effect on housing market supply and demand raises concerns, especially for contiguous areas. Many integration initiatives, such as cross-border amenity construction, infrastructure, and shared resources, contribute to promoting cooperation. This further attracts more outside investment, improves the employment rate and income levels, and accelerates labor mobility (World Bank, 2019; Buch et al., 2009; Kamau, 2010). Changes in employment, population mobility, and income, in turn, affect urban housing demand (Hui et al., 2011). Moreover, because of the growth potential of contiguous areas, speculative demands for housing increase and more outside investment flows into real estate, leading to an increase in housing supply (Zhou & Guo, 2015).

Second, targeted planning and policies for regional integration tend to trigger unintended spatial variation in housing prices. Public services and infrastructure are effectively improved in the whole area, depending on various regional initiatives, including the funding of infrastructure construction, and educational and medical development (Asher, 2010). The value of these improvements is capitalized into housing prices, which change consistently and globally. However, there are differences between areas in the spatial distribution of housing prices. The cross-border area is where the core city meets the contiguous areas and forms a new growth alliance (Tan et al., 2018), one that benefits more from regional integration planning than other types of areas. Therefore, in border areas both the quality and the layout of buildings and neighborhood amenities are better than in other areas. In border areas, following hedonic theory, high-quality housing characteristics ensure higher housing prices (Ooi et al., 2014).

Third, regional infrastructure provides an impetus for regional cooperation and development (Fujimura, 2004). The effect of these factors on housing prices has drawn considerable attention. Especially cross-border transportation, such as high-speed trains and highways, facilitate interregional interaction by reducing commuting costs. Compared with the core city, more cross-border transportation effects occur in contiguous areas, where transportation facilities make a greater contribution to improving regional accessibility (Vickerman, 2015). Therefore, the proximity to a cross-border transit station becomes a critical neighborhood attribute, which may have a positive or negative impact on housing prices (Andersson et al., 2010). In effect, the regional housing market is interrelated based on inter-city connections, which are even more evident for integrated regions (Holly et al., 2011; Zhang & Fan, 2019). To date, empirical work has mainly assessed associations between housing prices and regional integration in megacities such as the London metropolitan area and the Pan-Pearl River Delta. Results showed either a convergence or a diffusion of regional housing prices (Abbott & Vita, 2012; Gong et al., 2015). The change in house prices in major cities—for example, Beijing, Shanghai, and Hangzhou—has been explored, and the findings indicate that housing prices are frequently affected by urban factors as well as the spatial urban structure (Huang et al., 2017; Qin & Han, 2013; Wen & Tao, 2015). For contiguous cities, the spillover effects of the core city decay with distance, and thus housing prices in the border area are more affected and become the hotspots of housing price increases (Gong et al., 2016). However, limited attention has been paid to contiguous cities compared to core cities.

4.3 Materials and methods

4.3.1 Study area

Kaifeng is a medium-sized city in the province of Henan, bordering the provincial capital of Zhengzhou to the west. Until 2016, Kaifeng comprised five districts covering a total area of 1,849 km^2 and accommodating a population of 1.67 million. Kaifeng's gross domestic product increased from 22,624 billion yuan in 2001 to 193,495 billion yuan in 2016 (+15.38%). This rapid economic growth was associated with the ZKI project, which was launched in 2005. The integrated regions are parts of the Central Plains Urban Agglomeration, where Henan provincial and two municipal governments positively engage with the policy agenda to pursue cooperation and joint development.

To identify the impact of the ZKI on housing prices, we examined the five administrative districts (Figure 4.1) that were included in the first phrase of integration before 2014 (i.e., the districts of Longting, Shunhe, Gulou, Yuwangtai, and Jinming). Of these districts, Gulou and Longting are the most developed, whereas Shunhe and Yuwangtai are primarily comprised of urban villages and old houses. Jinming is positioned at the junction of Kaifeng and Zhengzhou and was a focus area of the ZKI project in 2005.

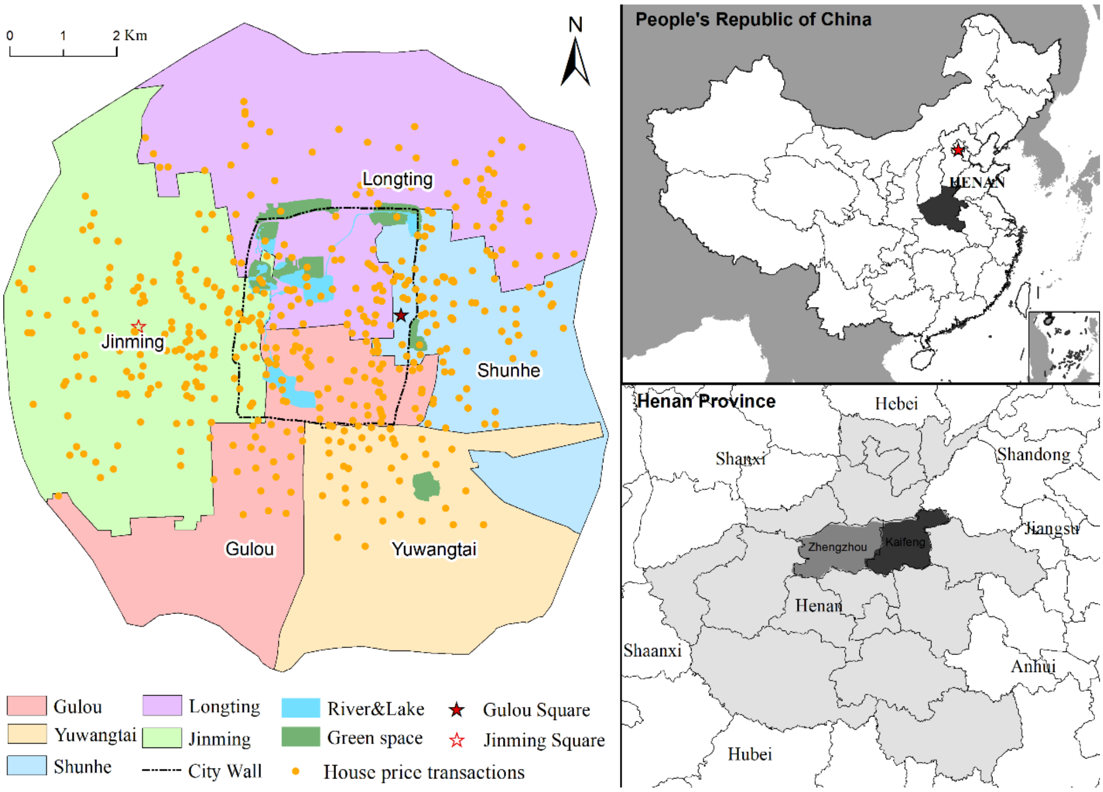

Figure 4.1 Study area

4.3.2 Data

4.3.2.1 Housing data

To establish the change in housing prices during the integration process and explore the dynamic effects of regional integration, we collected data from multiple sources. Data on annual average housing prices were obtained from the China Real East Statistical Yearbook and used to examine overall trends in housing prices in Zhengzhou and Kaifeng. Further, we obtained data on 1,556 new housing transactions from the Real Estate Transaction Management Center of Kaifeng. The data included housing price and physical properties (e.g., orientation and floor level). To represent the ZKI process, the housing transaction data covered four specific years—namely T_0 (2001), T_1 (2006), T_2 (2009), and T_3 (2016)—which represent the uninitiated, early, middle, and end of the ZKI project.

For each house, we derived structural, locational, neighborhood, and integration factors that are thought to be related to transaction prices (Helbich et al., 2014; Rosen, 1974; Yuan et al., 2018). The variables are summarized in Table 4.1. Table A 4.1 in the appendix presents the statistical description of all variables.

4.3.2.2 Zhengzhou and Kaifeng Integration factors

Data representing integration factors were compiled by quantifying governmental measures gathered from government websites (e.g., https://www.henan.gov.cn/; https://www.kaifeng.gov.cn/). The data covered the Zhengzhou–Kaifeng Expressway, the Jinming new town district, the new Jinming Square CBD, and the Z&K Light Rail Station. The following four integration factors were considered.

First, from 2005 to 2016, the government issued several policies and measures to boost inter-urban cooperation and integration. The development of new towns has a crucial influence on housing prices (Yuan et al., 2018). The Jinming new town district was originally designed in 2005 as the key development area of the ZKI in Kaifeng, connecting Kaifeng with Zhengzhou. The building standards of housing and public facilities in Jinming are in line with those in Zhengzhou and higher than those in the old town in Kaifeng. We expected housing prices to be higher in Jinming than in other areas.

Second, with the improvement of the residential environment and the increase in employment opportunities in Jinming, a new urban center (Jinming Square) was gradually developed. Jinming Square's positive effect on the prices of nearby housing was expected to become increasingly significant. Moreover, cross-border transportation facilitates regional cooperation and adds a premium to housing prices along the transportation route (Andersson et al., 2010; Fujimura, 2004).

Third, the Z&K Expressway, which links Zhengzhou with Kaifeng, was opened in 2006, formally marking the start of the ZKI era. The opening of the expressway reduced the commuting time from Zhengzhou to Kaifeng to approximately 1 hour. Because the population density is low along the Z&K Expressway, and referencing expressways' effective scope of influence reported in a previous study (Levkovich et al., 2016), we used a dummy variable for houses located within 1 km of the Z&K Expressway, thus ensuring a sufficiently large number of houses.

Fourth, the opening at the end of 2014 of the Z&K Light Rail, which reduced the commuting time to a mere 17 minutes, marked the end of the next phase of the ZKI. Based on the earlier finding that rail stations influence urban housing prices within a radius of approximately 1.8 km (Liu et al., 2015; Shi & Guo, 2009), and taking the local circumstances of Kaifeng into account, we employed a dummy variable to represent whether there was a light rail station within 2 km. This cross-border transportation infrastructure shortens the inter-urban spatiotemporal distance and supports population mobility, which we expected to influence housing prices.

4.3.2.3 Structural housing characteristics

Three of the physical properties of housing that play a vital role in housing prices—namely orientation, floor level, and floor area—served as structural variables. Besides the floor area of the apartment, residents generally favor a south-facing orientation, which provides better light conditions, and this may result in higher housing prices for units with this orientation (Jim & Chen, 2006). Although apartments on higher floors have better natural lighting and airiness, their location might make coming and going inconvenient, so the effect of floor level on housing prices is somewhat difficult to predict (Sirmans et al., 2005).

4.3.2.4 Locational characteristics

The accessibility of the CBD and the convenience of commuting contribute to increasing housing prices (McDonald & McMillen, 1990), which is likely to be related to the actual distance to the CBD and a transit station. However, some residents are unwilling to live near transit stations because of traffic noise and emissions (Jim & Chen, 2006). We included the straight-line distances from the apartment to Gulou Square and to the nearest bus station, as well as a dummy variable for the train station[2] (1 if the house is within 2 km, 0 otherwise), to represent locational advantage.

[2] Note, the train stations refer to the old Kaifeng railway station and not to Kaifengbei railway station. The latter was put into operation at the end of 2016.

4.3.2.5 Neighborhood characteristics

With improvements in the standard of living, people pay more attention to floor area ratio of buliding, educational quality, medical services, and nearby green landscapes, and these public amenities are capitalized into housing prices (Feng & Lu, 2013; Wen et al., 2015). Farmers' markets and department stores fulfil people's basic daily needs. Neighborhood attributes were straight-line distances to the nearest park or scenic spot, first-class hospital, farmers' market, department store or supermarket, and first-tier kindergarten, primary school, and junior high school. The accessibility of these locations was expected to have a positive impact on housing prices.

Table 4.1 Summary of residential characteristics and expected signs of the associations

Variables type	Abbreviation	Variable definition	Expected sign
Dependent variable	HP	The average apartment price (yuan/m^2)	
Zhengzhou and Kaifeng integration factors	NJM	1 if the apartment is located in new town Jinming district, 0 otherwise	+
	D_JMS	Distance from the apartment to the new CBD (Jinming Square) (in m, log-transformed)	-
	ZKEW	1 if the apartment is located within 1 km of Zhengzhou–Kaifeng Expressway, 0 otherwise	+
	ZKIR	1 if the apartment is located within 2 km of Zhengzhou and Kaifeng Light Rail station, 0 otherwise	+
Structural characteristic	OR	1 if the apartment has a south-facing orientation, 0 otherwise	+
	FL	Floor on which the apartment is located	+/-
	FL_AR	The total floor area of the apartment (in m^2, log-transformed)	+
Location characteristic	D_GLS	Distance from the apartment to the old CBD (Gulou Square) (in m, log-transformed)	+
	D_BS	Distance from the apartment to the nearest bus station (in m, log-transformed)	+
	TS	1 if the apartment is located within 2 km of the train station, 0 otherwise	+/-

Neighborhood characteristic	D_PSS	Distance from the apartment to the nearest park or scenic spot (in m, log-transformed)	-
	FAR	The ratio of the building's floor area to the gross lot area (log-transformed)	-
	D_HOSP	Distance from the apartment to the nearest hospital (in m, log-transformed)	-
	D_FM	Distance from the apartment to the nearest farmer's market (in m, log-transformed)	-
	D_DS	Distance from the apartment to the nearest department store and supermarket (in m, log-transformed)	-
	D_KG	Distance from the apartment to the nearest kindergarten (in m, log-transformed)	-
	D_PS	Distance from the apartment to the nearest primary school (in m, log-transformed)	-
	D_JHS	Distance from the apartment to the nearest junior high school (in m, log-transformed)	-

4.3.3 Statistical analyses

4.3.3.1 Baseline hedonic price model

A baseline hedonic price model establishes a relationship between housing prices and a bundle of attributes by estimating the implicit prices of different attributes (Yu et al., 2007). To examine the effects of the ZKI on housing prices, we assessed hedonic price models in each of the four specific periods separately. To stabilize the variance while improving the goodness-of-fit, we applied the following logarithmic equation:

$$\ln p_{it} = \beta_{0t} + \beta_{1t} ZKEW_{it} + \beta_{2t} D\_JMS_{it} + \beta_{3t} NJM_{it} + \beta_{4t} ZKIR_{it} + \mathbf{k}_{it}\mathbf{X}_{it} + \varepsilon_{it}$$
$$(\mathrm{t} = \mathrm{T}_0, \mathrm{T}_1, \mathrm{T}_2, \mathrm{T}_3) \quad (1)$$

Where t is set as T_0, T_1, T_2, and T_3, respectively, and p_{it} refers to the housing prices of dwelling i in t year. ZKI factors include ZKEW, D_JMS, NJM, and ZKIR; $\boldsymbol{X}$ comprises the structural, neighborhood, and location control variables; β_0, β_1, β_2, β_3, and β_4 are the estimated coefficients, and $\boldsymbol{K}$ is the i *1 vector of the coefficients of control variables; ε is an error term.

4.3.3.2 Special model with interaction terms

To overcome an endogenous bias and further distinguish the changes in the influence of integration factors on housing prices in different periods, we took T_1[3] (2006) as the baseline year and fitted a model with interactions between the quantitative variables of the ZKI and a time dummy variable (i.e., ZKEW * T_2 (ZK2), D_JMS * T_2 (ZM2), NJM*T_2 (ZY2), ZKEW * T_3 (ZK3), D_JMS * T_3 (ZM3), and NJM * T_3 (ZY3)). Three models were constructed using the pooled cross-sectional data in the periods $T_1 + T_2$ (2), $T_2 + T_3$ (3), and $T1 + T_2 + T_3$ (4).

$$\ln p_i = \beta_0 + \beta_1 ZKEW + \beta_2 D\_JMSz + \beta_3 NJM + \delta_1 T_2 + z_1 ZKEW * T_2 + z_2 D\_JMS * T_2$$
$$+ z_3 NJM * T_2 + \mathbf{k}_i \mathbf{X}_i + \varepsilon \quad (2)$$

$$\ln p_i = \beta_0 + \beta_1 ZKEW + \beta_2 D\_JMS + \beta_3 NJM + \beta_4 ZKIR + \delta_1 T_3 + z_1 ZKEW * T_3 +$$
$$z_2 D\_JMS * T_3 + z_3 NJM * T_3 + \mathbf{k}_i \mathbf{X}_i + \varepsilon \quad (3)$$

$$\ln p_i = \beta_0 + \beta_1 ZKEW + \beta_2 D\_JMS + \beta_3 NJM + \beta_4 ZKIR + \delta_1 T_2 + \delta_2 T_3 + z_1 ZKEW * T_2$$
$$+ z_2 D\_JMS * T_2 + z_3 NJM * T_2 + z_5 D\_JMS * T_3 + z_6 NJM * T_3 + z_7 ZKEW * T_3$$
$$+ \mathbf{k}_i \mathbf{X}_i + \varepsilon \quad (4)$$

[3] The integration of Zhengzhou and Kaifeng began in 2005. Integration factors were observed from 2006.

where p_i indexes the housing price, and T_2 and T_3 are the time dummy variables for 2009 and 2016, respectively.

4.3.3.3 Spatial econometric model

Spatial autocorrelation may be observed in the prices of nearby housing, but the traditional ordinary least squares (OLS) method neglects this fact, leading to biased results. To assess whether the OLS residuals are spatially correlated, the Moran's *I* statistics and the Lagrange multiplier (LM) diagnostics for residual spatial dependence were assessed. In the case of significant residual spatial autocorrelation, two alternative model specifications were fitted, namely the spatial lag model (SLM) and the spatial error model (SEM) (Yu et al., 2007).

First, the SLM assumes that housing prices depend on nearby housing prices and hedonic features:

$$\ln p = \rho Mp + X\beta + \varepsilon \qquad (5)$$

Second, the SEM is primarily applied when spatial autocorrelation exists among the residuals and is given as:

$$\ln p = X\beta + \mu; \qquad \mu = \rho M\mu + \varepsilon \qquad (6)$$

For the above formulae, $p(n\times1)$ is the dependent variable; $X(n\times k)$ represents the independent variables; $\beta(n\times1)$ is the coefficient to be estimated; ε is an error-disturbance term; ρ and λ are the spatial autoregressive and residual spatial autoregressive coefficients, respectively; and M is the spatial weight matrix. To specify the weight matrix, we followed Chi (2013) and used k-nearest neighbor weight matrix. As sensitivity analysis, we estimated the models with different values for k ranging from 3 to 8.

4.4 Results and Discussion

4.4.1 Changing housing prices in the context of Zheng & Kai Integration

Figure 4.2 provides an overview of housing sales in Kaifeng from 2001 to 2016. The total sales area increased by 15.5 times between 2001 and 2016, namely from 0.3 million to 4.65 million square meters. The total sales price increased by 66.12 times in the same period, that is, from 3.31 billion to 218.87 billion yuan. After 2005, both total sales prices and total sales area continued to rise in Kaifeng, demonstrating that real estate investment and consumption were stimulated after the ZKI was implemented.

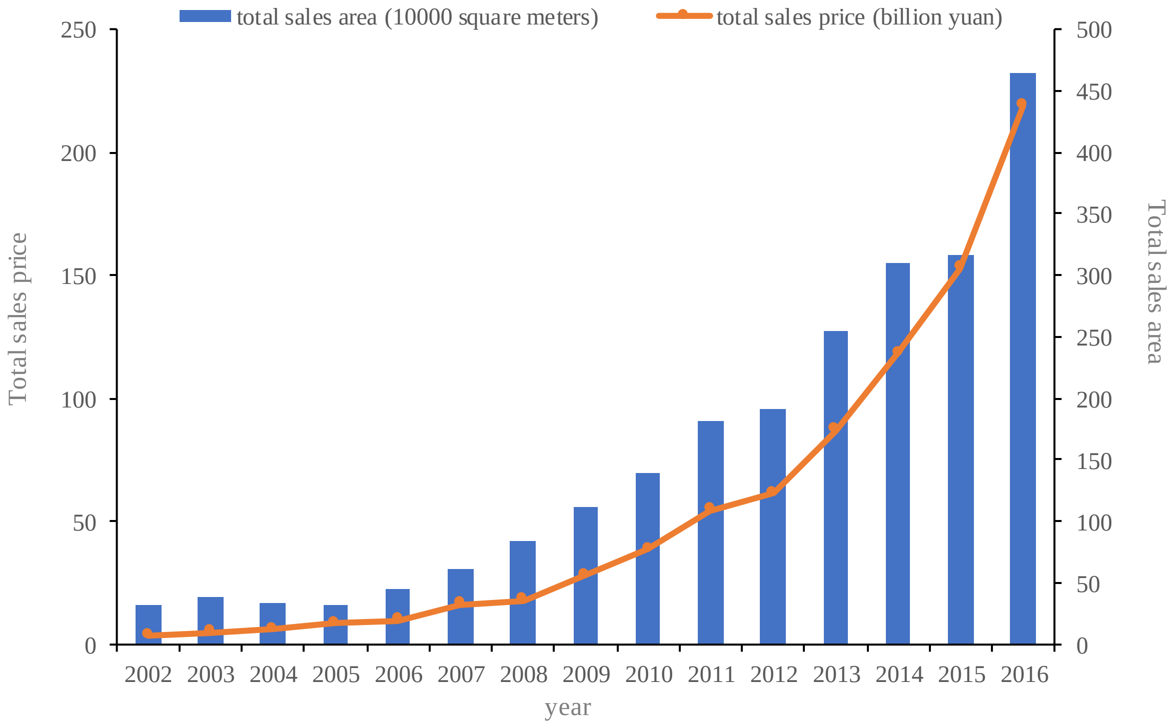

Figure 4.2 Total sales areas and housing prices in Kaifeng, 2001–16

Figure 4.3 shows the annual change in the housing market from 2001 to 2016 in Kaifeng and Zhengzhou. In Kaifeng, the average price increased by 5.47 times between 2001 and 2016, namely from 889 yuan/square meter to 4,864 yuan/square meter. The annual growth rate showed significant short-term fluctuations, and the floating range decreased after 2009, with an average growth rate of 13.12% from 2001 to 2016. Compared with Zhengzhou, the housing market in Kaifeng indeed lost momentum. The price gap between the two cities widened slightly over time. This is consistent with findings based on the Yangtze River Delta, where the gap in housing prices across cities also widened during the integration process (Song & Liu, 2018) and the gap in annual growth rates narrowed. Surprisingly, after 2009, the development focus in Zhengzhou shifted to the new Zhengdong District, inter-urban cooperation strengthened, and the trends in growth rate continued consistently.

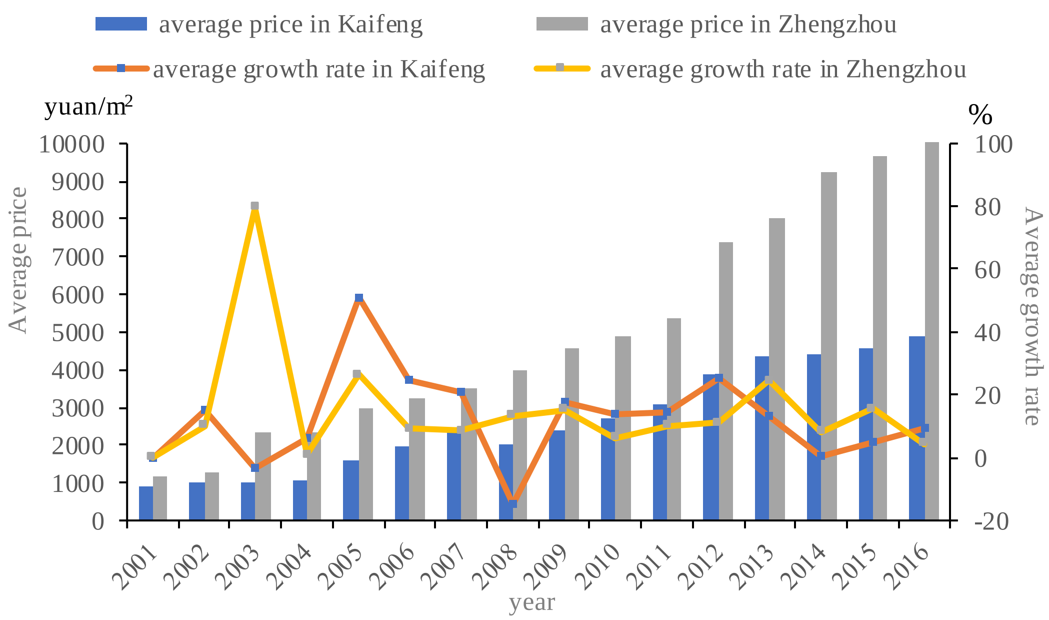

Figure 4.3 Average housing prices and average growth rates in Zhengzhou and Kaifeng, 2001-16

Before the ZKI was proposed, the two cities developed independently. The average housing price and the average growth rate were significantly higher in Zhengzhou than in Kaifeng. After the ZKI, there was rapid growth in housing prices in Kaifeng, with the average housing price increasing more rapidly in Kaifeng than in Zhengzhou, especially in 2005. Government measures, including the Z&K Expressway and the approval of the Z&K Industrial Belt, gave rise to population mobility and industrial development across the two cities. After 2007, the growth rate declined because of a lack of substantive progress. Regional infrastructure—including finance and telecoms—realized the planned integration, the construction of the industrial belt began, and the ZKI was upgraded to a national strategy. Housing prices saw further growth from 2009 to 2013. Although tight government housing policies, such as purchase restrictions and property taxes, prevented housing prices from soaring in 2014, the development of new amenities, such as the Z&K Light Rail and an inter-urban dedicated logistics channel, provided another boost in housing prices.

4.4.2 Dynamic impact of Zheng & Kai Integration on housing prices

Tables 4.2 and 4.3 summarize the results obtained from the hedonic models. The variance inflation factors for all variables were below the critical value of 3, indicating that multicollinearity was not an issue. The adjusted R^2 indicated moderate model fits. However, given that spatial dependence existed in 2006, 2009, and 2016 (Models 2–4), as confirmed by significant Moran's I statistics (all $p< 0.01$), we fitted SEMs and SLMs to account for spatial autocorrelation. The significance levels of the lag coefficients ρ and λ for Models 2–7 were below 0.01, indicating the existence of spatial dependence. The log likelihood values for SLM and SEM were larger than those for the basic OLS, whereas the Akaike information criterion (AIC) and the Schwarz criterion (SC) values for the spatial models were considerably lower, indicating a better model fit than the OLS models. The three fit measures (LIK, AIC, and SC) consistently showed that the SEM performed better than the SLM. Hence, the results of the SEM are further discussed.

According to hedonic price theory, housing attributes play an important role in determining housing prices (Table 4.2). First, regarding structural attributes, floor level and floor area were, as expected, significantly and positively associated with housing prices, and a southern orientation enhanced the comparative advantage of the housing unit. A significant decrease in the coefficient for floor area ratio indicates the importance of the communal environment for residents (Yuan et al., 2018). Moreover, with respect to locational attributes, the coefficient of Distance to the old Gulou CBD changed from negative to positive between 2009 and 2016, reflecting a decline in the importance of Gulou Square. This result is possibly related to planning practices in Kaifeng; that is, most of the streets surrounding Gulou Square are under preservation orders—which means that both building renovation and population density are limited—and the area has been designated by the local government as a critical tourist center. In addition, as a result of the urban center being transposed from Gulou to Jinming in Kaifeng and the increasing employment opportunities and convenient services, housing prices increased in Jinming (Wen & Tao, 2015). No significant effect was found for Distance to train station. The significant negative coefficient of Distance to bus station in 2001 was in line with expectations; the insignificant positive coefficients of Distance to bus station in 2006 and 2009 may be linked to the increase in the number of private cars. In 2016, urban environment renovation and restrictions on private cars promoted a reconsideration of the demand for public transportation (Xu et al., 2015). In line with earlier studies (Li et al., 2016; Yuan et al., 2018), we found that neighborhood attributes, such as parks and scenic areas, hospitals, department stores, and supermarkets, were significantly positively associated with housing prices. Reflecting parents' increasing concern about their children's education, the capitalization effect of kindergartens in Kaifeng was more significant and positive compared to the effects of primary and junior high schools. The effect of farmers' markets on nearby housing prices became negative, possibly because the construction of community vegetable markets replaced the demand for farmers' markets.

Table 4.2 shows that the integration measures had different impacts on housing prices in each period of the integration project (2006, 2009, and 2016). The SEM results show significantly positive coefficients of Near Z&K Expressway, indicating that the Z&K Expressway was positively associated with housing prices across the integration periods. Similar to Fujimura (2004)'s findings, cross-border transportation played an increasingly important role in residents' lives and in regional cooperation. The Z&K Expressway facilitated convenient transportation between Zhengzhou and Kaifeng. The decreasing positive coefficient of Distance to the new Jinming Square CBD from 2006 to 2016 indicates that the effect of Jinming faded with urban development. Jinming was the future growth pole of Kaifeng in the early period of the ZKI, and Jinming's development potential attracted large numbers of investment-oriented purchasers from Zhengzhou, in addition to local homebuyers. However, as the integration advanced, Jinming became the main activity area in Kaifeng, with high population density, and its sufficient housing supply may have reduced the attraction of the new town. The decreasing coefficient of Distance to the new Jinming Square CBD implies that homebuyers increasingly preferred to live near Jinming Square and enjoy more convenient services. This conclusion is supported by the spatial distribution of high prices in 2009 and 2016. Until 2016, the significant positive coefficient of Near Z&K Light Rail indicates that the Z&K Light Rail contributed to increases in housing prices, which supports the conclusion that there is a positive relationship between light rail and housing prices (Lin et al., 2018). Overall, the ZKI had a significant and positive effect on housing prices in Kaifeng.

Table 4.2 Regression results for housing prices in each period

Model	M1 (2001)	M2 (2006)			M3 (2009)			M4 (2016)		
Method	OLS	OLS	SLM	SEM	OLS	SLM	SEM	OLS	SLM	SEM
Constant	7.345***	4.376***	7.40***	4.84***	6.893***	5.628***	6.877***	7.355***	5.641***	7.357***
ZKEW	#	0.092**	0.089***	0.091**	0.141**	0.147***	0.152**	0.04***	0.036**	0.038*
D_JMS	#	0.073	0.025*	0.017*	-0.138***	-0.138***	-0.138***	-0.030**	-0.027**	-0.030**
NJM	#	0.159***	0.155***	0.149***	0.079*	0.080*	0.078*	0.044**	0.043**	0.044***
ZKIR	#	#	#	#	#	#	#	0.028*	0.031*	0.030*
OR	0.293***	0.306**	0.309**	0.309**	0.402***	0.421***	0.420***	0.293***	0.286***	0.291***
FL	-0.074***	-0.051***	-0.051***	-0.051***	0.141***	0.141***	0.139***	0.012***	0.012***	0.011***
FL_AR	0.100***	0.336***	0.334***	0.348***	0.259***	0.256***	0.259***	0.111***	0.110***	0.111***
PR	-0.056*	-0.188***	-0.188***	-0.185***	-0.044***	-0.043***	-0.042**	-0.118***	-0.116***	-.117***
D_GLS	-0.166**	-0.0701**	-0.074***	-0.057***	-0.002	-0.008	-0.004	0.152***	0.124***	0.149**
D_BS	-0.018*	-0.018	-0.016	-0.030	0.037	0.038	0.039	-0.020**	-0.020***	-.021***
TS	-0.033	0.032	-0.042	-0.029	-0.052	-0.048	-0.051	-0.038	-0.035	-0.035
D_PSS	0.109**	-0.051**	-0.054***	-0.072***	-0.094***	-0.091***	-0.091**	-0.028***	-0.026*	-0.026*
D_HOSP	0.035	-0.053**	-0.054**	-0.048**	-0.047	-0.046*	-0.047*	-0.061***	-0.063***	-.062***
D_FM	-0.155***	0.079***	0.083***	0.102***	0.034**	0.033	0.034	0.047	0.046**	0.046**
D_DS	-0.016	-0.036*	-0.035*	-0.047***	0.044***	0.047	0.045	-0.037**	-0.054*	-.036**
D_KG	0.099*	0.000	0.005	0.007	-0.097*	-0.095***	-0.094***	-0.011*	-0.011*	-0.011*
D_PS	-0.116*	0.0356	0.036	0.005	0.122**	0.118**	0.124***	0.019	0.018	0.020

D_JHS	0.03	0.025	0.035	0.067**	-0.016	-0.014	-0.014	0.004	0.003	0.005
ρ	-	-	0.137***	-	-	0.382***	-	-	0.224**	-
λ	-	-	-	0.116***	-	-	0.218***	-	-	0.124**
Adjusted R^2	0.276	0.570	-	-	0.441	-	-	0.545	-	-
Log likelihood	-128.93	36.213	36.294	37.74	-185.112	-183.962	-184.230	161.368	163.385	161.55
AIC-score	287.87	-36.426	-34.588	-41.705	406.224	405.924	404.462	-284.736	-286.771	-285.107
SC-score	340.08	35.996	31.857	30.716	478.338	472.045	476.576	-204.811	-202.639	-205.182
Moran's I	0.094	0.037**	-	-	0.018***	-	-	0.118***	-	-
N	240	413	413	413	406	406	406	497	497	497

Signif. codes : '***' 0.001; '**' 0.01; '*' 0.05.

Further, we estimated the changes in the effects of the integration factors on housing prices using one specific model. Table 4.3 shows the regression results of Models 5–7, with time variables (T_2 and T_3) included to control for the time effect on housing prices. We used the interaction terms between the quantitative planning variables and the time dummy variables to examine whether each phased effect of the ZKI was significantly different. Given that the Z&K Light Rail was opened at the end of 2014, its impact on housing prices could only be examined in the later period (T_3), so we excluded interactions with ZKIR. The OLS, SLM, and SEM models were applied in the specific regression analysis. The SEM was found to have the best model fit.

Table 4.3 Dynamic influence of regional integration on housing prices

Model	M5 (2006+2009)			M6 (2009+2016)			M7 (2006+2009+2016)		
Method	OLS	SLM	SEM	OLS	SLM	SEM	OLS	SLM	SEM
Constant	6.969***	5.133***	6.969***	7.566**	7.962***	7.635***	5.336**	5.420***	5.494***
T_2 (2009)	0.257**	0.298**	0.202**	#	#	#	0.232***	0.230***	0.214***
T_3 (2016)	#	#	#	0.088***	0.095***	0.096***	0.064***	0.064***	0.066***
ZK2	0.117***	0.072***	0.041**	#	#	#	0.116**	0.116**	0.106**
ZM2	-0.051***	-0.071***	-0.069***	#	#	#	-0.026***	-0.026***	-0.029***
ZY2	0.009***	0.005***	0.016***	#	#	#	0.008***	0.007***	0.012***
ZK3	#	#	#	-0.136	-0.136**	-0.138**	-0.061*	-0.061**	-0.066**
ZM3	#	#	#	-0.101***	-0.101***	-0.107***	-0.092*	-0.091***	-0.092***
ZY3	#	#	#	0.086*	0.080*	0.081*	-0.069**	-0.069**	-0.075**
ZKEW	0.134**	0.132**	0.131***	0.211***	0.212***	0.019***	0.122***	0.122**	0.112**
D_JMS	-0.168***	-0.148***	-0.180***	-0.174***	-0.174***	-0.178***	-0.029**	-0.029**	-0.030**
NJM	0.185***	0.179***	0.011***	0.016	0.017	0.023	0.134***	0.134***	0.136***
ZKIR	#	#	#	0.015***	0.018*	0.014*	0.019*	0.019*	0.021***
OR	0.329***	0.323***	0.323***	0.410**	0.412***	0.405**	0.332***	0.332***	0.335***
FL	0.040***	0.039***	0.039***	0.039***	0.039***	0.038***	0.014***	0.014***	0.014***
FL_AR	0.341***	0.329***	0.327***	0.195***	0.196***	0.190***	0.257***	0.257***	0.255***
PR	-0.134***	-0.133***	-0.140***	-0.103***	-0.104***	-0.101***	-0.136***	-0.136***	-0.136***
D_GLS	-0.013	-0.016	-0.019	0.021	0.037	0.021	0.030	0.021	0.013
D_BS	-0.016*	-0.004	-0.003*	0.002***	-0.003	0.002	-0.013*	-0.014*	-0.009**
TS	-0.055	-0.058*	-0.066*	-0.053*	-0.056*	-0.052*	-0.054**	-0.055**	-0.054**
D_PSS	-0.072***	-0.074***	-0.095**	-0.050***	-0.050***	-0.059***	-0.048***	-0.048***	-0.060***
D_HOSP	-0.092***	-0.078***	-0.033*	-0.039**	-0.037*	-0.039*	-0.050***	-0.086***	-0.044**

D_FM	0.047**	0.043*	0.060*	0.020	0.021	0.024	0.041**	-0.05***	0.044**
D_DS	-0.047***	0.038*	0.017	0.008	0.007	-0.000	0.005	0.005	-0.003
D_KG	-0.042***	-0.029***	-0.030***	-0.052***	-0.051***	-0.051***	-0.030**	-0.031***	-0.028**
D_PS	0.120***	0.101***	0.108	0.088***	0.093*	0.089***	0.077***	0.079**	0.082***
D_JHS	-0.042	-0.047*	-0.033*	0.015	0.018	0.026	0.002	0.002	0.007
ρ	-	0.240***	-	-	0.071***	-	-	0.014***	-
λ	-	-	0.453***	-	-	0.273***	-	-	0.361***
Adjusted R^2	0.366	-	-	0.724	-	-	0.785	-	-
LL	-323.523	-319.217	-318.764	-262.142	-261.77	-260.469	-324.394	-324.363	-322.55
AIC	691.047	684.433	681.528	570.285	569.539	566.939	702.789	701.726	699.111
SC	794.625	792.719	785.106	680.791	678.85	677.445	842.692	841.811	839.014
N	819	819	819	903	903	903	1316	1316	1316

Signif. codes: '***' 0.001; '**' 0.01; '*' 0.05.

In Model 5, the coefficient of T_2 was 0.257, meaning that the overall housing price was 22.38% higher (exp (0.257) − 1) (Halvorsen & Palmquist, 1980) in T_2 than in T_1. In Model 6, the coefficient of T_3 was 0.096, meaning that the overall housing price increased by 5.02% between T_2 and T_3. Similar results are shown in Model 7, indicating that housing prices in Kaifeng had an increasing trend during the integration process, despite the decline in growth rate.

Model 7 is a nested extension of Models 5 and 6 with three complete periods of the ZKI using the full sample of housing prices. We selected this model to examine the changes in the effect of the ZKI on housing prices. At T_1 (2006), the coefficients of the integration factors Near Z&K Expressway, Distance to the new Jinming Square CBD, and Located in Jinming new town district were 0.112, -0.030, and 0.136, respectively, and all were significant below the 0.1 level. At T_2 (2009), the corresponding coefficients changed to 0.218 (0.112 + 0.106), -0.059 (-0.03 − 0.029), and 0.148 (0.136 + 0.012). These results show that the implemented integration measures—especially the increased efficiency of the Z&K Expressway—had a growing positive influence on housing prices in Kaifeng. At T_3 (2016), the coefficients of Near Z&K Expressway and Distance to the new Jinming Square CBD were 0.046 and 0.061, respectively, representing increases from T_2 but decreases from T_1. The coefficient of Distance to the new Jinming Square CBD decreased to -0.122 at T_3, indicating that the impact of Distance to the new Jinming Square CBD on housing prices increased. The coefficient of Near Z&K Light Rail was 0.021, which was significant at $p < 0.01$, showing a positive and significant effect of the Z&K Light Rail on housing prices.

Throughout the process, the Z&K Expressway, Jinming Square, and Jinming new town positively influenced housing prices, and the premium effect of Jinming Square increased with the expansion of Jinming. However, the effects of the Z&K Expressway and Jinming new town declined somewhat from 2009 to 2016. A significant positive effect was also found for the Z&K Light Rail, probably because people prefer to purchase housing near the Z&K Light Rail, which reduces intercity commuting time to 17 minutes, rather than near the Z&K Expressway. The interactions between the three quantitative planning variables and T_2 (ZK2: 0.106, ZM2: -0.029, ZY2: 0.012) were all larger than the corresponding interactions with T_3 (ZK3: -0.066, ZM3: -0.092, ZY3: -0.075), indicating that the capitalization effects of the Z&K Expressway and Jinming new town declined, whereas the positive effect of Jinming Square grew as the integration advanced. These results show that the ZKI accelerated the construction of Jinming new town, and that Jinming Square replaced Gulou Square as the new urban center. Homebuyers thus prefer to live near the new CBD rather than elsewhere in Jinming. Cross-border transportation including the Z&K Expressway and the Z&K Light Rail also played a critical role in the changing housing prices and urban development during the ZKI process. Overall, the ZKI facilitated urban development, improved urban amenities, and influenced urban housing prices.

4.5 Conclusions

The present study investigated the effect of regional integration on the dynamics and determinants of housing prices in Kaifeng city (China) between 2001 and 2016. The housing market in Kaifeng has undergone restructuring in the context of the Zheng & Kai Integration (ZKI) project. Since the integration was implemented, the real estate market has boomed in Kaifeng, and the difference between Zhengzhou and Kaifeng in annual growth rate has declined. Our results suggest that residents of the core city increasingly prefer to purchase properties in contiguous cities, due to the unaffordable price of housing in Zhengzhou and reduced cross-border commuting costs (Lin et al., 2018). In addition, contrary to the belief that within metropolitan areas, core cities have a negative effect on their neighboring small and medium-sized cities (Wang, 2015), Kaifeng benefited from the integration with the core city Zhengzhou. As expected, housing prices in Kaifeng showed newly emerging hotspots in border areas, deviating from the conventional core–periphery model of a single city. The regional integration resulted in new growth poles within the border area of Kaifeng.

Moreover, the regression results confirm earlier findings regarding the Guangzhou metropolitan area (He, 2017), namely that housing prices were influenced by regional integration factors, and especially cross-border transportation. We found that the total capitalization impact of cross-border transportation is gradually decomposed into various modes of outbound traffic with the improvement of the transportation system. The positive influence of the Z&K Expressway on housing prices declined slightly, while that of the Z&K Light Rail increased dramatically. Thus, in line with the study by Lin et al. (2018) on the

Shenzhen–Dongguan–Huizhou metropolitan area, the time-saving capacity of cross-border traffic is particularly attractive for residents in integrated regions.

Meanwhile, urban development driven by the integration (e.g., the building of a new district) was another critical determinant of housing prices. The construction of residential districts, industrial districts, and commercial areas in Jinming promoted the formation of the new urban center of Jinming Square, which echoes the notion of "zone fever" and "project fever" in urban China (Wang, 2015). The local government formulates urban planning strategies concerning the ZKI; for instance, it focuses on westward development, pushing the development of the new Jinming district, and connecting new urban centers with Zhengzhou. Thus, the coordination of multilevel governments plays an important role in driving regional cooperation and local urban development (Luo & Shen, 2009).

As evidenced by our findings, cross-border traffic is an important channel of interregional interaction. Improving the intercity transportation system for integrated regions, reduces commuting time, supports the flow of capital, labor, and information, and strengthens regional cooperation. In addition, building a new urban district in a small to medium-sized city relieves pressure on inner-urban housing prices. In the long run, due to the important role of small to medium-sized cities, infrastructure upgrades will be necessary to counteract spatially uneven housing prices.

Our study contributes to a better understanding of the evolution of housing prices in the context of regional integration, exemplifies the quantification of integration and the selection of methods, and provides a research perspective for evaluating the effectiveness of regional integration policies. However, our study had some limitations. First, the regression analysis considered only a limited number of housing characteristics and integration factors. Future studies should include additional socioeconomic and more policy-related factors as control variables. Second, the study covered four periods of the ZKI cross-sectionally. A longitudinal study design covering the entire integration period from 2001 to 2016 would enable a more precise analysis of house price dynamics.

4.6 Appendix

Table A 4.1 Descriptive statistics

	Minimum	Maximum	Mean	S.D.
T_0 (*N*=240)				
Housing price	101.69	1760	776.094	343.917
ZKEW	#	#	#	#
D_JMS	#	#	#	#
NJM	#	#	#	#
ZKIR	#	#	#	#
OR	0	1	0.2	0.401
FL	1	7	3.53	1.80
FL_AR	3.109	6.684	4.541	0.447
FAR	-2.303	2.826	0.597	1.012
D_GLS	5.428	8.677	7.721	0.647
D_BS	3.683	8.261	7.035	0.975
TS	0	1	0.225	0.418
D_PSS	4.073	8.359	6.793	0.986
D_HOSP	3.775	8.204	6.601	0.705
D_FM	4.874	9.943	7.034	0.680
D_DS	3.294	7.521	6.300	0.777
D_KG	3.516	7.060	5.748	0.667
D_PS	3.543	7.132	6.240	0.548
D_JHS	3.588	7.467	6.282	0.673

T_1 (*N*=413)				
Housing price	289.15	2669.29	1422.081	375.788
ZKEW	0	1	0.082	0.275
D_JMS	6.282	8.979	8.104	0.547
NJM	0	1	0.354	0.479
ZKIR	#	#	#	#
OR	0	1	0.007	0.085
FL	1	7	3.259	1.590
FL_AR	3.651	5.428	4.642	0.241
FAR	-0.967	2.333	1.893	0.896
D_GLS	5.509	8.985	7.764	0.679
D_BS	3.574	7.841	6.678	0.864
TS	0	1	0.138	0.345
D_PSS	3.095	8.506	6.855	1.095
D_HOSP	4.771	8.317	6.844	0.684
D_FM	2.255	8.067	7.101	0.633
D_DS	2.939	7.704	6.460	0.832
D_KG	2.877	7.140	5.810	0.708
D_PS	4.698	7.901	6.464	0.480
D_JHS	4.014	7.831	6.492	0.604
	Minimum	Maximum	Mean	S.D.
T_2 (*N*=406)				
Housing price	300	3773.9	1981.625	794.743

ZKEW	0	1	0.098	0.298
D_JMS	5.230	9.8	7.993	0.700
NJM	0	1	0.350	0.477
ZKIR	#	#	#	#
OR	0	1	0.020	0.139
FL	1	7	3.241	1.589
FL_AR	3.457	6.221	4.704	0.278
FAR	-0.968	3.268	1.287	0.819
D_GLS	5.255	8.788	7.837	0.638
D_BS	2.949	7.860	6.539	0.898
TS	0	1	0.241	0.428
D_PSS	3.094	8.771	7.005	1.031
D_HOSP	3.972	8.370	6.718	0.848
D_FM	2.255	8.061	7.126	0.628
D_DS	3.272	7.685	6.523	0.818
D_KG	2.121	7.140	5.747	0.648
D_PS	3.768	7.820	6.383	0.566
D_JHS	3.774	7.801	6.395	0.770
T_3 (*N*=497)				
Housing price	2187.5	12000	4854.879	1256.693
ZKEW	0	1	0.237	0.426
D_JMS	5.252	8.960	7.510	0.748
NJM	0	1	0.368	0.482

ZKIR	0	1	0.368	0.482
OR	0	1	0.074	0.263
FL	1	26	3.229	2.118
FL_AR	3.651	5.953	4.634	0.266
FAR	-0.968	2.333	1.710	0.934
D_GLS	6.404	10.506	8.339	0.488
D_BS	3.004	8.152	6.189	1.065
TS	0	1	0.070	0.256
D_PSS	-2.198	8.985	7.605	1.023
D_HOSP	4.173	8.918	7.432	0.896
D_FM	3.617	8.733	7.432	0.716
D_DS	3.689	8.474	7.017	0.792
D_KG	-2.924	8.222	6.278	0.962
D_PS	3.785	8.404	6.922	0.773
D_JHS	3.953	8.505	7.019	0.885

Chapter 5 Club Convergence of Regional Housing Prices in China: Evidence from 70 Major Cities

This chapter is based on the article: Cai, Y., Zhu, Y., & Helbich, M. (2022). Club convergence of regional housing prices in China: evidence from 70 major Cities. The Annals of Regional Science, 69(1), 33

ABSTRACT

House prices in China have increased greatly in recent decades and the dynamics seem to vary across cities. It is rational to assume that urban housing prices converge to different equilibria and form club convergence (i.e., subgroups). Empirical evidence on the existence of club convergence is limited, however, as is evidence on the underlying mechanisms. Therefore, the aim of the present study was to 1) detect club convergence in housing prices across Chinese regions over the period 2006–17, and 2) examine the determinants influencing club formation. A log *t* test in combination with a clustering algorithm was used to assess club formation. The results showed that regional housing prices face heterogeneous dynamics, providing some evidence of housing market segmentation. Four convergence clubs of Chinese regions with different convergence levels were identified. Ordered logit model showed that population growth, income, and housing regulation are among the drivers of club formation. The results also indicated that being in a different Chinese city-tier and differences in urban healthcare affect housing market club membership. The findings are supportive for policymakers to coordinate balanced regional housing development across China.

Keywords: Convergence clubs; Log *t* test; Housing price dynamics; China

5.1 Introduction

The relatedness of regional housing prices is one of the core topics in research on subnational housing price dynamics and the matter has attracted interest from both scholars and policymakers (Grigoryeva & Ley, 2019; Meen, 1999, 2016; Zhang & Fan, 2019). However, empirical evidence on regional housing prices is mixed. While some studies have identified the long-term convergence of regional housing prices (Holmes & Grimes, 2008; Meen, 2002), others found that prices differ across regions (Abbott & Vita, 2012, 2013; Holly et al., 2011). Recently, scholars have questioned whether absolute convergence and divergence exists across regional housing prices and instead favor club convergence (i.e., convergence in multiple subgroups). Evidence from a few developed countries, namely the UK, the USA, Spain, and Australia, support club convergence (Churchill et al., 2018; Blanco et al., 2016; Kim & Rous, 2012; Montagnoli & Nagayasu, 2015).

The market-oriented reform of the Chinese housing system coupled with ongoing urbanization has resulted in a rapidly growing housing market. Since 2005, China's housing market has boomed. For example, the average annual growth rate of housing prices in 2005–17 was nearly 9%—an increase of 3.7% over 1998–2004. In this, the interrelation of housing prices across regions played an important role (Mao, 2016). Not only does the booming housing market pose the risk of housing price bubbles (Rong et al., 2016), but also differences in regional housing prices increase wealth disparities due to varying economic developments and geographical differences[1], including access to amenities and restrictions caused by the household registration system, (i.e., Hukou[2]) (Gong et al., 2016; Mao, 2016; Wen & Tao, 2015; Zhang & Fan, 2019).

Facing the risk of overinflated housing markets and heterogeneity in housing prices across Chinese regions, the dynamic relationship of regional housing prices requires closer attention

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[1] Areas in the east show significantly higher house prices than those in central or western China and cities being ranked high in Chinese city-tier have higher housing prices and growth.

[2] The Hukou (i.e., the household registration) is initially used to monitor population movement in China. Nowadays it is also an instrument to prevent rural-urban migratory flows and inter-cities' labor mobility.

to prevent housing bubbles (Holmes et al., 2018), uncover disparities across regional housing markets (Alexander & Barrow, 1994), and provide the foundation for regionally diversified and locally oriented adjustment policies.

So far, only a few studies have identified a common equilibrium state across regional housing prices in China (Gong et al., 2016; Lee et al., 2016; Zhang & Morley, 2014). For example, Mao (2016) found evidence for regional housing prices divergence based on the monthly panel data of 70 cities. Liu et al. (2018) examined structure convergence and indicated different orders of convergence across regional housing prices and that price transmission occurs from eastern to central and western China. However, club convergence has been poorly assessed in China.

To address this knowledge gap, we adopted a recently introduced panel convergence test (Phillips & Sul, 2007, 2009) to explore the transitional dynamics and individual heterogeneity of housing prices. First, we used housing price trends between 2006 and 2017 to analyze the pattern of convergence across the 70 major cities in China. Second, we investigated potential drivers of club formation by means of an ordered logit model (Blanco et al., 2016; Holmes et al., 2019).

Our study makes three main contributions to the literature. First, it is among the first to explore the club convergence of regional housing prices in a developing country. Second, it provides new evidence regarding the formation process of the convergence of housing prices among regions in China. It allows the identification of groups of regions with similar housing price growth paths and growth trajectories per club. Third, it identified key drivers that explain the convergence clubs in regional housing prices.

This paper is structured as follows. Section 2 summarizes the literature, Section 3 tests club convergence, Section 4 identifies the determinant of club formation, and Section 5 concludes.

5.2 Literature review

5.2.1 Theoretical background to the convergence of regional housing prices

Early studies used convergence to address economic growth based on multiple growth theory (Barro & Sala-i-Martin, 1992; Baumol, 1986). While empirical evidence on regional housing price convergence is mounting, the focus has mainly been on particular forms of convergence (i.e., stochastic, β-, σ-, and club convergence) (Gray, 2018). Economically, stochastic convergence shows that per capita income tends toward a long-term steady-state without other conditions (Carlino & Mills, 1993; Quah, 1992). Further, neoclassical growth theory divides convergence into σ-convergence and absolute and conditional β-convergences. In particular, σ-convergence shows that cross-sectional income dispersion across a region decreases over time (Barro & Sala-i-Martin, 1992), while β-convergence—including absolute and conditional β-convergence—refers to a negative correlation between growth and income. Absolute β-convergence indicates that the difference in income between rich regions and poor regions with high-growth rates decreases (Barro & Sala-i-Martin, 1992; Baumol, 1986), while conditional β-convergence refers to a relation between growth and income after controlling for steady state (Barro & Sala-i-Martin, 1992). Note that β-convergence is a necessary, but not a sufficient, condition for σ-convergence (Young et al., 2008). Club convergence means that the per capita income across regions with similar initial conditions and sectional characteristics display different clusters (Chenery et al., 1986; Rostow, 1980).

Similarly, in housing markets, stochastic convergence—which is also called non-conditional convergence—indicates that regional housing prices tend toward a single equilibrium in the long run (Meen, 1999). This is reflected by a regression coefficient describing average behavior, and has no other limit condition such as similar characteristic across regions. Further, σ-convergence and β-convergence express two sub-forms of convergence according to the growth behavior of housing prices across regions and stress the distribution dynamics (Cook, 2012). In contrast, club convergence, which is a type of conditional convergence, states that multiple subgroups exist; namely, cities with similar attributes are categorized into one club (Kim & Rous, 2012). Studies have addressed the long-term convergence of housing prices (i.e., stochastic convergence) (Holmes & Grimes, 2008), while other forms of convergence are underrepresented.

5.2.2 Convergence pattern of regional housing prices

The literature on the convergence behavior of housing prices is inconclusive (Cook, 2012; Kim & Rous, 2012; Zhang & Morley, 2014). Although stochastic convergence has been assessed through different approaches (e.g., unit root testing and pair-wise analysis) (Cook, 2003, 2005; Holmes & Grimes, 2008; Holmes et al., 2017; Meen, 2002), the results are partly contradictory. For example, the study by Holmes et al. (2011) confirmed the long-term convergence of regional housing prices in the USA, while Abbott and Vita (2012, 2013) found no evidence of a long-term equilibrium between housing prices in Greater London. Findings such as these raised doubts concerning the existence of stochastic convergence (Barros et al., 2012), and sparked interest in alternative forms of convergence in regional housing prices, including σ- and β-convergence (Cook, 2012): Regarding the β- and σ-convergence of regional housing prices, Cook (2012) showed by means of a conditional probabilistic approach that β-convergence, but not σ-convergence, existed across the UK housing market cycle.

With increasing regional housing market segmentation, the club convergence of regional housing prices mainly in Western developing countries is a newly explored area (Apergis & Payne, 2012; Kim & Rous, 2012; Montagnoli & Nagayasu, 2015; Montañés & Olmos, 2013; Tsai, 2018). Kim and Rous (2012) explored quarterly housing price indices and found multiple convergence clubs across US states and metropolitan areas. Blanco et al. (2016) identified convergence clubs among Spanish regions based on housing price trends between 1995 and 2007. In addition, Tsai (2018) found the convergence change for housing prices in European countries during various periods of regional integration at the supra-national level, while Holmes et al. (2019) found club formation of housing prices in England and Wales at an inter-city level. However, evidence of such from developing regions is scarce.

5.2.3 Drivers of regional housing price convergence

Apart from consistently exploring the convergence pattern of regional housing prices, a number of empirical studies have attempted to explore the determinants of regional housing price convergence. First, most studies found that social economy and housing market factors—such as population, economic condition, housing supply, and credit availability—drive regional housing price convergence (Holmes et al., 2017; Lee & Chien, 2011; Meen, 1999; Tsai, 2018). Meen (1999) originally pointed out that interregional migration, equity transfer, and spatial arbitrage causes long-term convergence across regional housing prices. Work by Lee and Chien (2011) testing the stationarity of Taiwan's regional housing prices showed that in regions with similar economic development, housing prices are more likely to form convergence. By testing the club convergence of the USA, Kim and Rous (2012) confirmed that housing supply regularly drives price convergence. Second, geographical physical attributes—such as the location, distance, and grouping of cities—have received more attention (Abbott & Vita, 2012; Blanco et al., 2016; Holmes et al., 2011). By testing the long-term convergence in the USA and Paris, France, Holmes et al. (2011, 2017) found that the inverse relationship between distance and the speed of convergence, namely the linking of housing prices, is closer between adjacent than non-adjacent regions. Compared with the economic and demographic factors at the national scale in the USA, Barros et al. (2012) found that specific factors at the state level have more influence on housing price convergence across states. Zhang et al. (2019) examined the short-term convergence dynamics of China's regional urban housing market and found that urban hierarchy and core–periphery significantly affect the convergence tendency. Third, urban amenity—including nature conditions and public goods—have also been shown to determine housing price convergence (Holmes et al., 2019; Kim & Rous, 2012). For instance, Kim and Rous (2012) indicated that urban climate is an important driver of convergence club formation across regional housing prices in the USA, while Holmes et al. (2019) found that transportation congestion, crime rates, and education have a significant influence on the club convergence of local housing prices in England and Wales.

5.3 Materials and methods

5.3.1 The log t convergence test and club clustering algorithm

To examine club convergence, we used panel data and applied the log *t* test and club clustering algorithm (Phillips & Sul, 2007, 2009). The log *t* test assesses relative convergence, while clustering identifies convergence subgroups, whereas club members are tested by a merging procedure.

This model uses a panel data $P_{it,}$ where i = 1, …, N represents the number of individuals, and t = 1, …, T denotes the observed time. P_{it} is the logarithmic housing price index in a city i at time t. P_{it} is decomposed into systematic components, g_{it}, and transitory components, a_{it}:

$$P_{it} = g_{it} + a_{it} \qquad (1)$$

To separate the common from the idiosyncratic components, P_{it} can be reformulated in terms of the time-varying common factor representation as given in Equation (1):

$$P_{it} = \frac{g_{it} + a_{it}}{u_t} u_t = \delta_{it} u_t \quad \text{for all } i \text{ and } t \qquad (2)$$

Where u_t and δ_{it} are both time-varying elements. u_t is a common trend component in the panel and δ_{it}, refers to a loading coefficient—an idiosyncratic element that measures the relative share of u_t of a city i. Hence, δ_{it} captures the relative transition path of a city i as it moves relative to a common growth path determined by u_t. Equation (2) enables convergence testing by examining δ_{it} convergence. Thus, the dynamic behavior of δ_{it} is modeled semi-parametrically as:

$$\delta_{it} = \delta_i + \zeta_{it}[\sigma_i / L(t)t^{\alpha}] \qquad (3)$$

Where the fixed term, $\zeta_{it} \sim iid\ (0,1)$ across i may be weakly dependent over t and the function $L(t)$ is a slow varying over t ($L(t) \rightarrow \infty$ *as* $t \rightarrow \infty$) such as $L(t) = \log t$, and the rate parameter α denotes the convergence rate when $\alpha \geq 0$. Hence, Equation (3) ensures that δ_{it} converges to δ_i for all $\alpha \geq 0$.

Phillips and Sul (2007) designed a log t test to examine the null hypothesis of convergence for at least one i as follows:

$$X_0 : \delta_i = \delta \quad \text{and} \quad \alpha \geq 0 \qquad (4)$$

against the alternative:

$$X_A : \delta_i \neq \delta \quad \text{for} \ \forall\, i, \quad \text{or} \ \alpha < 0 \qquad (5)$$

There are three steps for the log t test. First, calculating the cross-sectional variance ratio H_1/H_t:

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it}-1)^2 \qquad (6)$$

Where h_{it} is the relative transition parameter and depicts an individual trajectory for each i relative to the panel average, that is:

$$h_{it} = \frac{P_{it}}{N^{-1}\sum_{i=1}^{N} P_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N}\delta_{it}} \qquad (7)$$

which removes the common factor u_t by scaling, measures the loading coefficient δ_{it} relative to the cross-sectional average, and describes the relative departure of city i from the common growth path, u_t. When each city moves toward one common transition path, $\delta_i \rightarrow \delta$, thus, $h_{it} \rightarrow 1$ for all i, and $H_t \rightarrow 0$ as $t \rightarrow \infty$.

Following Phillips and Sul (2007), we set $L(t) = log\ (t+1)$ in Equation (3), and fitted the following log t regression,

$$\log(H_1/H_t) - 2\log L(t) = \hat{a} + \hat{b}\log t + u_t,$$
$$t = [vT], [vT]+1, \ldots, T \qquad \text{with } v \in (0,1) \qquad (8)$$

Where a fraction vT of the sample is used to analyze. Based on Monte Carlo simulations, the trimming parameter $v \in (0.2, 0.3)$ shows a satisfying model performance. In particular, it is recommended to set $v = 0.3$ for the small or moderate T (≤ 50) sample and set $v = 0.2$ for the large T (≥ 100) sample (Du, 2017; Phillips & Sul, 2007).

The estimated coefficient $\hat{b} = 2\hat{\alpha}$ and $\hat{\alpha}$ refer to the estimated rate parameter α in X_0. Note that the magnitude of the parameter $\hat{b}$ has a positive correlation with the rate of convergence.

In the context of Equation (8), the null hypothesis is tested by the following weak inequality:

$$X_0 : b \geq 0, \qquad X_A : b < 0 \qquad (9)$$

Finally, we tested the inequality part of the null hypothesis X_0 by applying a traditional one-sided t test with a heteroskedasticity and autocorrelation consistent standard error. Utilizing the t-statistic $t_{\hat{b}}$, the null hypothesis is rejected when $t_{\hat{b}} < -1.65$ at the 5% level.

Even though the null hypothesis X_0 could be rejected, convergence in subgroups among cities may exist. Based on the repeated log t test, Phillips and Sul (2007) further provide a clustering procedure to identify convergence clubs. However, as the procedure is conservative, probably leading to leading to inappropriate sub-clubs, a merging procedure can limit the number of clubs (Phillips & Sul, 2009). According to the algorithm adjustment from Schnurbus et al. (2017), the clustering algorithm comprises the following five steps (Du, 2017).

Step 1: Eliminating the cycle by the filter method, eliminating high volatility by discarding the v fraction of the remaining for the sample, and ordering the final panel observations (i.e., cities).
Step 2: A core group of cities is determined according to the maximum t_k with t_k >-1.65 and by conducting the log t test for the first k ($2 \leq k < N$) cities sequentially.
Step 3: Each remaining city is examined individually by the log t regression. A new city is added to the core group (i.e., the first sub-convergence group) if the corresponding t-statistic > -1.65.
Step 4: Conducting the log t regression examines the remaining cities in step 3. The second convergence group is identified if the null hypothesis is not rejected. Otherwise, steps 1–3 are repeated to detect sub-convergence clubs. When no core group appears in step 2, the algorithm terminates.
Step 5: Performs the log t regression for the first two subgroups. If the joint t-statistic > -1.65, the subgroups are merged and form a new first club, and continue with the log t regression for the new first club and the third subgroup. Otherwise, the log t regression is conducted for the second and third subgroups. The procedure is performed iteratively and results in new convergence clubs (Du, 2017).

5.3.2 Study area and data

The availability of long time-series data allowed us to investigate China's 70 major cities. The cities were assessed by multiple indicators, including economic level, urban population, and city size and influence, covering the 1st-tier, new 1st-tier, 2nd-tier, 3rd-tier, and 4th-tier cities. The selected panel data reflect the dynamic of regional housing prices across China. We considered 9,940 monthly housing price indices of new housing units over the period March 2006–December 2017 (142*70, T_0 = 142). Data were obtained from the National Bureau of Statistics of

China. The housing price indices were divided by the figures for March 2006, multiplied by 100 for normalization, and then converted into the logarithm form ($log(p_{it}*100/p_{i1})$) (Apergis et al., 2015). As done elsewhere (Holmes et al., 2019), we used a filter method[3] (Hamilton, 2018) to smooth cyclical components of the logarithmic price indices (T_1 = 118; the first 24 monthly observations were discarded). This approach overcomes the spurious dynamic relationship arising from the traditional Hodrick–Prescott filter (Hodrick & Prescott, 1997). To eliminate the base year problem[4] of index prices, a fraction of the observations (i.e., the first 47 monthly observations of T_1; see Figure 5.1) was discarded based on the steady performance of the relative transition curves of the 70 cities (Phillips & Sul, 2007). In total, 6,650 monthly price index series from February 2010 to December 2017 were examined (T = 95). Figure 5.1 shows various city-based transition curves illustrating the time-series and cross-sectional heterogeneity in Chinese housing prices.

[3] To circumvent spurious dynamic relations in a traditional HP filter, Hamilton (2018) proposed using an OLS regression of variable g on a constant and the p lag term of g (the value p depends on the date type). The fitted values are used as an estimate of the latent cyclical component.

[4] For house price index data, when the first time of the observation is set as the base year, one trend component will appear for the calculated data because of the influence of the same initial condition.

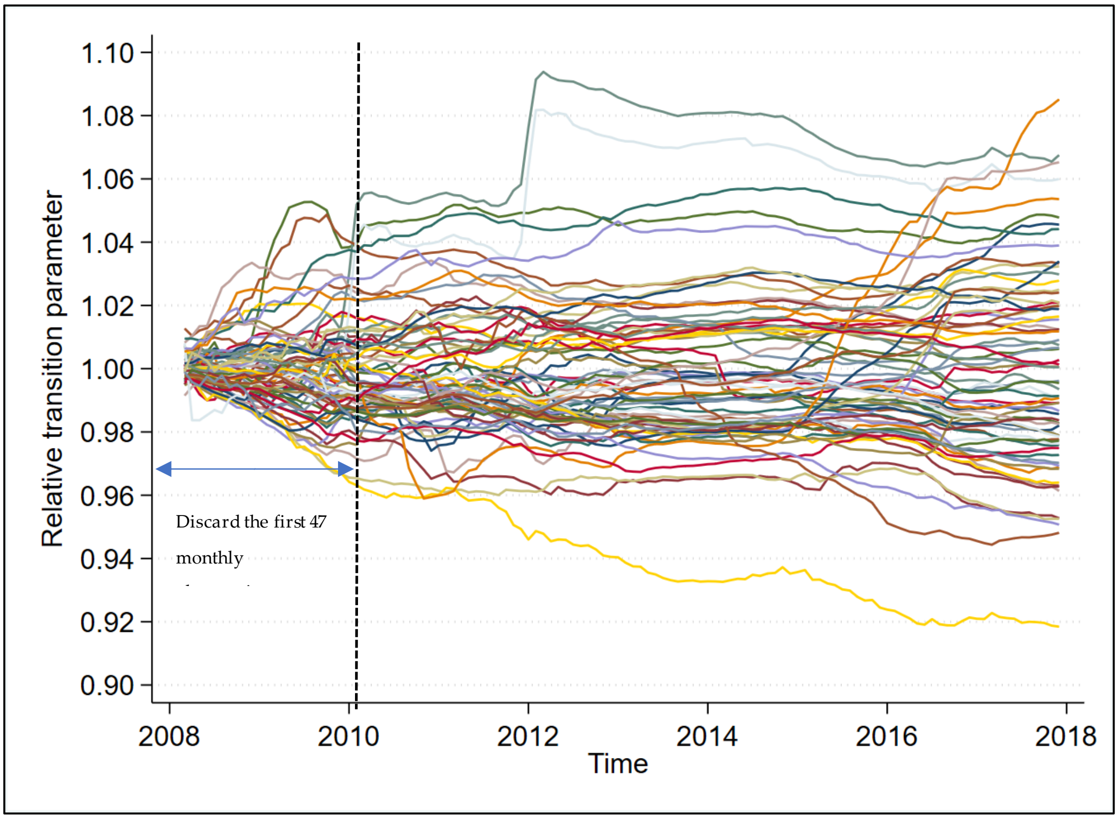


Figure 5.1 Relative transition curves (h_{it}) of cities and the base year effect (Note: $\boldsymbol{h_{it}} = \frac{\boldsymbol{P_{it}}}{\boldsymbol{N^{-1}\sum_{i=1}^{N} P_{it}}}$, where $P_{it} = log(p_{it}*100/p_{i1})$ and is then processed through Hamilton's (2018) filter using a panel of house prices indices from February 2010 to December 2017.)

Figure 5.2 shows the variation coefficient for housing prices across cities between February 2010 and December 2017. It also shows that long-term σ-convergence may not exist, and that the dispersion across regional prices is volatile.

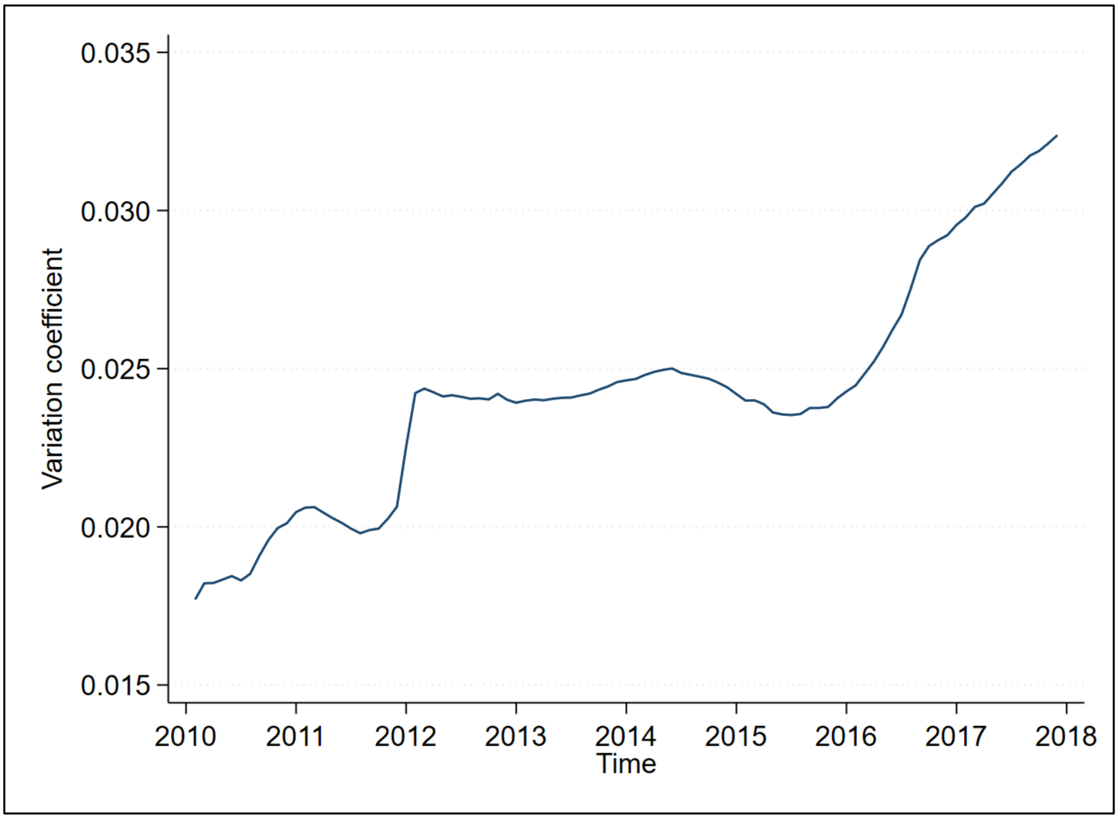


Figure 5.2 House price dispersion across China's 70 major cities based on the variation coefficient, February 2010–December 2017

5.4 Results

5.4.1 Convergence club in regional housing prices

By applying the log t test to housing prices based on $v = 0.2$[5], the first 19 months of the sample T are discarded. The estimate of b is negative (-0.912) with a t-statistic less than -1.65 (-63.257) suggesting housing price divergence. This result confirms not only Figures 5.1 and 5.2 but also an earlier study (Mao, 2016).

We found six convergence clubs in the initial classification; these were merged into four clubs (Table 5.1). With respect to the final club, the slope coefficient $\hat{b}$ for Club 2, Club 3, and Club 4 are significant and positive, and the members converge conditionally at different price levels. Club 1 consists of 34 major cities. The slope coefficient $\hat{b}$ is -0.143 and the t-statistic in Club 1 is

[5] We discarded a fraction ($v = 0.2$) of the time series in terms of the size ($T = 95$, > 50). Setting $v = 0.22$, 0.24, 0.26 and 0.30 was used to check for robustness.

-1.277, indicating that the 34 cities converge into a weak club (Phillips & Sul, 2009). Club 2 comprises 19 cities. The slope coefficient $\hat{b}$ is 0.107 with a t-statistic of 1.361, which indicates that regional housing prices in Club 2 are approaching one another (α = 0.054). Club 3 consists of 14 cities merging the memberships of the initial clubs 3–5. The slope coefficient $\hat{b}$ is 0.076 with a t-statistic of 1.575. Club 3 shows a slow convergence speed relative to Club 2 (α = 0.038). Club 4 contains 3 cities of the initial club 6. The $\hat{b}$ value is 0.498 with a t-statistic of 3.316. The convergence speed of Club 4 (α = 0.249) is faster than that of other clubs.

Table 5.1 Convergence club classification: The results of log *t* regression and club clustering and merging

Initial club classification

Club	No.	$\hat{b}$	*t*-stat.	Club members
1	34	0.056	-1.277	Beijing, Shanghai, Tianjin, Guangzhou, Shenzhen, Shijiazhuang, Nanjing, Xi'an, Wuhan, Changsha, Xiamen, Fuzhou, Zhengzhou, Sanya, Haikou, Hefei, Nanchang, Beihai, Nanning, Lanzhou, Urumchi, Xining, Yantai, Huizhou, Yinchuan, Jining, Yueyang, Zhanjiang, Dalian, Guiyang, Mudanjiang, Ningbo, Shenyang, Yichang
2	19	0.051	1.361	Hangzhou, Chongqing, Chengdu, Xuzhou, Jinan, Changchun, Harbin, Bengbu, Ganzhou, Changde, Jilin, Kunming, Luoyang, Pingdingshan, Anqing, Qinhuangdao, Taiyuan, Xiangyang, Zunyi
3	9	0.873	2.930	Dali, Jinhua, Yangzhou, Jiujiang, Wuxi, Guilin, Nanchong, Hohhot, Dandong
4	2	0.514	0.014	Qingdao, Luzhou
5	3	0.189	2.061	Baotou, Quanzhou, Shaoguan
6	3	1.800	3.316	Tangshan, Wenzhou, Jinzhou

Final club classification

Club	Log *t* regression				Descriptive statistics		
	Initial club	No.	$\hat{b}$	*t*-stat.	Average house price index 2010	Average house price index 2017	Average monthly growth rate 2010–2017
1	1	34	-0.143	-1.277	4.835	5.145	0.066%
2	2	19	0.107	1.361	4.750	4.935	0.035%
3	3+4+5	14	0.076	1.575	4.722	4.853	0.029%

4	6	3	0.498	3.316	4.721	4.706	-0.004%
Members of the final clubs							
Club 1	Beijing, Shanghai, Tianjin, Guangzhou, Shenzhen, Shijiazhuang, Nanjing, Xi'an, Wuhan, Changsha, Xiamen, Fuzhou, Zhengzhou, Sa nya, Haikou, Hefei, Nanchang, Beihai, Nanning, Lanzhou, Urumchi, Xining, Yantai, Huizhou, Yinchuan, Jining, Yueyang, Zhanjiang, Da lian, Guiyang, Mudanjiang, Ningbo, Shenyang, Yichang						
Club 2	Hangzhou, Chongqing, Chengdu, Xuzhou, Jinan, Changchun, Harbin, Bengbu, Ganzhou, Changde, Jilin, Kunming, Luoyang, Pingdingshan, Anqing, Qinhuangdao, Taiyuan, Xiangyang, Zunyi						
Club 3	Dali, Jinhua, Yangzhou, Jiujiang, Wuxi, Guilin, Nanchong, Hohhot, Dandong, Qingdao, Luzhou, Baotou, Quanzhou, Shaoguan						
Club 4	Tangshan, Wenzhou, Jinzhou						

Notes: No. is number of city members. The log t test is distributed as a one-sided t-statistics with a 5% critical value of -1.65.

Based on the average house price index of each club (Table 5.1), the panel contains one high price growth club, two medium growth clubs, and one low growth club. As Figure 5.3 shows, the cities with the highest price growth rate are included in Club 1. The price growth in cities in Club 2 is lower than that in cities in Club 1, with a pronounced gap between the two clubs. The growth dynamic for cities in Club 3 is similar to that of cities in Club 2. Cities in Club 4 have the lowest price growth.

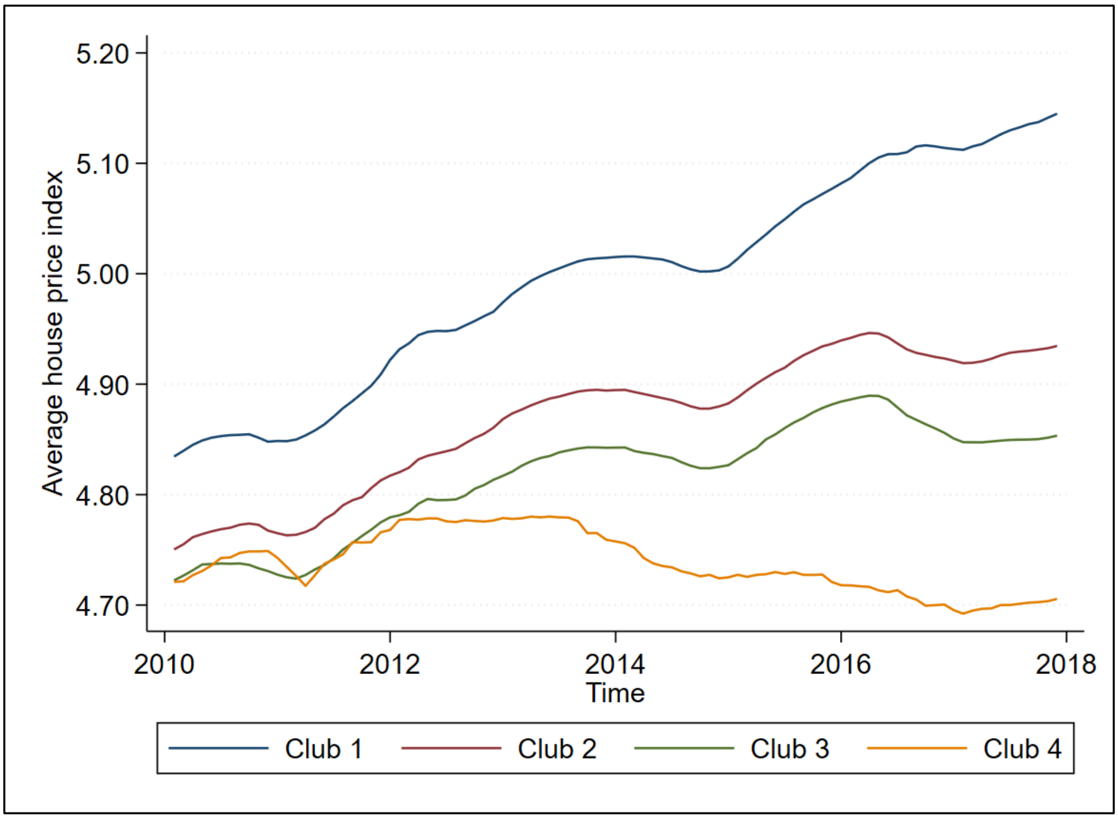


Figure 5.3 The dynamic path of average logarithmic house price index for each final club

Figure 5.4 shows the spatial distribution of the members of the final clubs. Unlike previous studies (Zhang & Fan, 2019), we found it difficult to discover a specific spatial pattern between club memberships, though the geographical and socioeconomic attributes are rather similar (Liu et al., 2018). The Moran's I statistics confirm that the clubs are spatially randomly distributed (Club 1: $I = 0.076$, $p = 0.298$; Club 2: $I = 0.030$, $p = 0.489$; Club 3: $I = 0.080$, $p = 0.285$; Club 4: $I = -0.214$, $p = 0.348$). The cities belonging to Club 1 include Beijing, Tianjin, and Shanghai, and most provincial capitals, coastal areas (e.g., Zhanjiang, Ningbo, Yantai, and Huizhou), and river cities (e.g., Yichang and Mudanjiang). Compared with other clubs, the majority of members of Club 1 are 1st-tier or new 1st-tier cites. Apart from Hangzhou, Chongqing, and Chengdu, Club 2 mainly consists of capital cities located in the center and northeast—such as Jinan, Taiyuan, Changchun, and Harbin—and some economically powerful prefectural cities in various provinces. Club 3 includes numerous smaller and less developed regions that are 3rd-tier or 4th-tier cities, and several wealthy regions like Qingdao, Wuxi, and Jinhua. Members of Club 4 are coastal cities, of which Wenzhou, Tangshan, and Jinzhou are 2nd-tier, 3rd-tier and 4th-tier cities, respectively. In short, our results show that developed cities (e.g., those in Club 1) more easily converge toward one club, while the convergence speed is slower compared to the less developed cities.

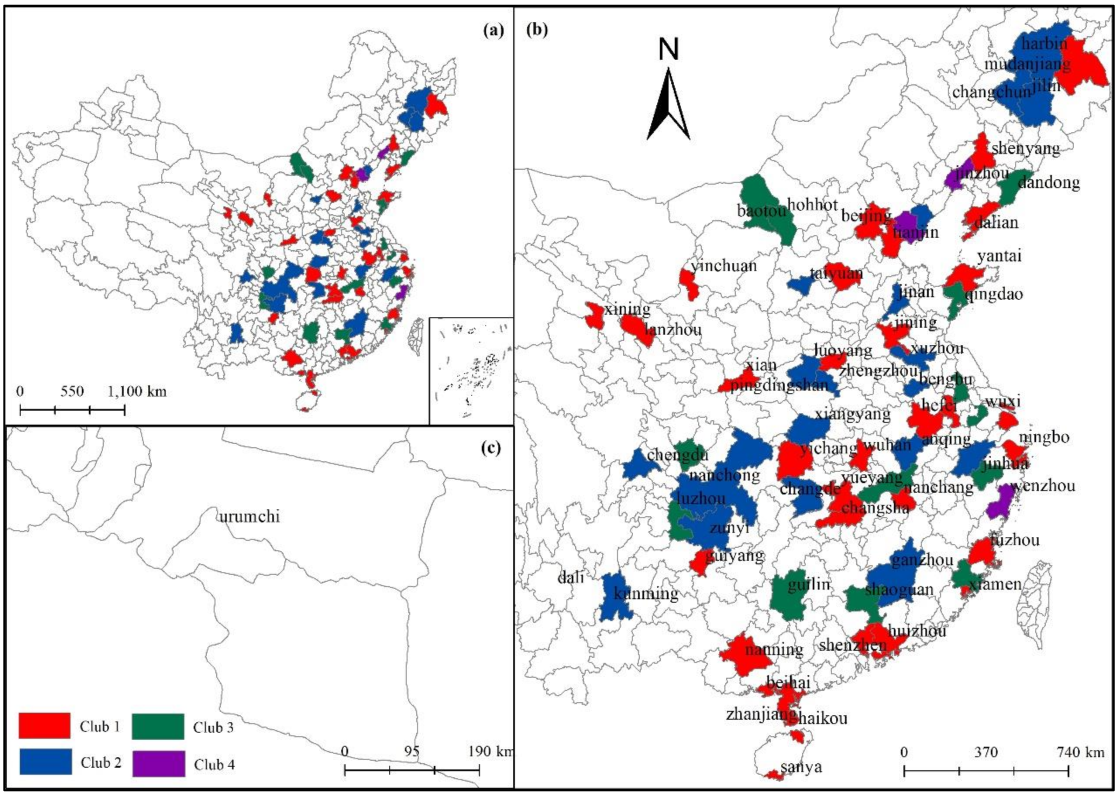


Figure 5.4 The spatial distribution of the final convergence clubs for regional house prices in China

Further, our results indicate that our convergence club classification is not entirely compatible with the traditionally defined economic regions in China (Liu et al., 2018; Zhang & Fan, 2019; Zhang et al., 2016; Zhang et al., 2017). The results in Table 5.2 show that after executing the log *t* test for regional housing prices based on the regional definition of city tier (i.e., the 1st-/new

1st-/2nd-/3rd-/4th-tier city) and geographical division (i.e., Eastern/Central/Western), the *t*-statistic values for all region subgroups are less than -1.65, meaning that there is no evidence of convergence across those regions.

Table 5.2 The results of log *t* test based on the divisions of city tier and geographical location

City tier division	*t*-stat.	Geographical division	*t*-stat.
1st-tier cities	-4.740	Eastern areas	-32.486
New 1st-tier cities	-55.720	Central areas	-59.568
2nd-tier cities	-22.370	Western areas	-41.960
3rd-tier cities	-6.496		
4th-tier cities	-24.582		

Note: The numbers are *t*-statistics for the slope coefficients from estimating log *t* test model by setting $v = 0.2$.

5.4.2 Transitional behavior

Housing prices in the 70 cities do not converge to the same level. Nevertheless, under the assumption of club convergence, we established the relative transition paths for four final clubs by calculating the cross-sectional mean of their relative transition paths (Figure 5.5). There seems to be no tendency toward convergence across clubs. Club 1 is above the average (1.00) with an upward tendency. The other three clubs remain below the average. Clubs 2 and 3 both show a slight downward trend, while the transition path of Club 2 tends to be similar to that of Club 3. Although Club 4 departs from a similar initial value as Club 3, it has a pronounced downward trend.

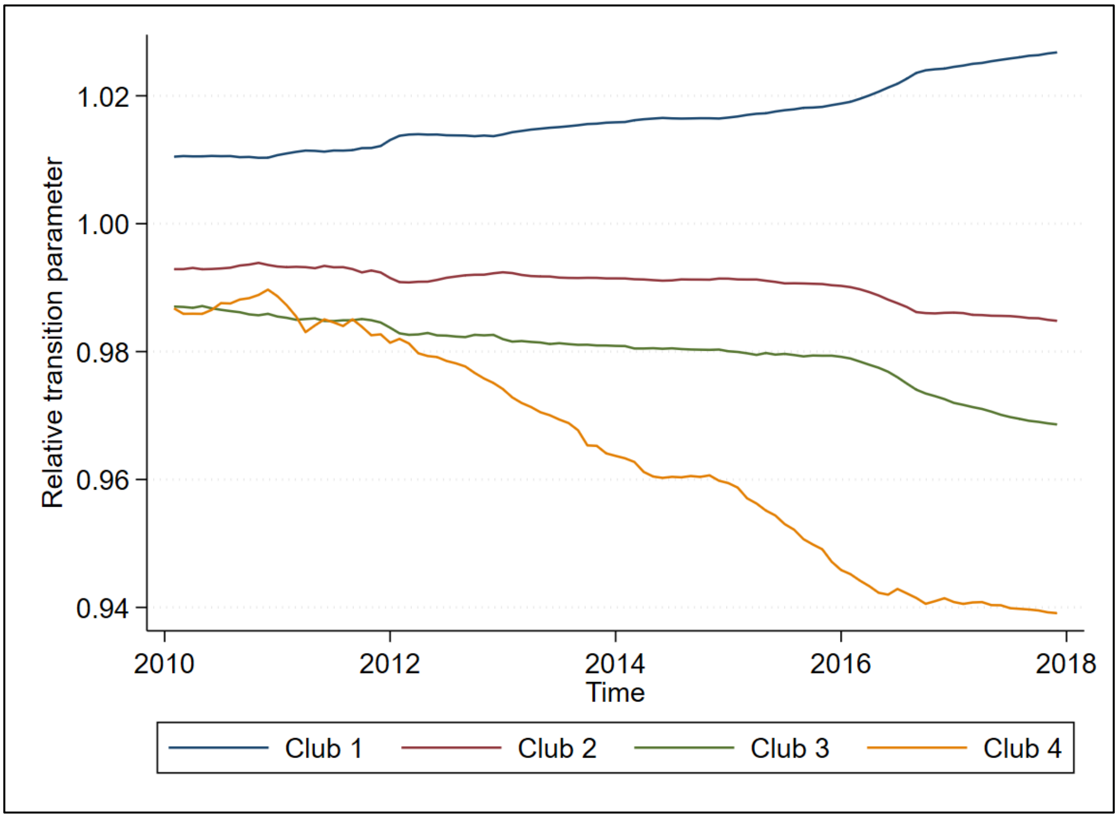
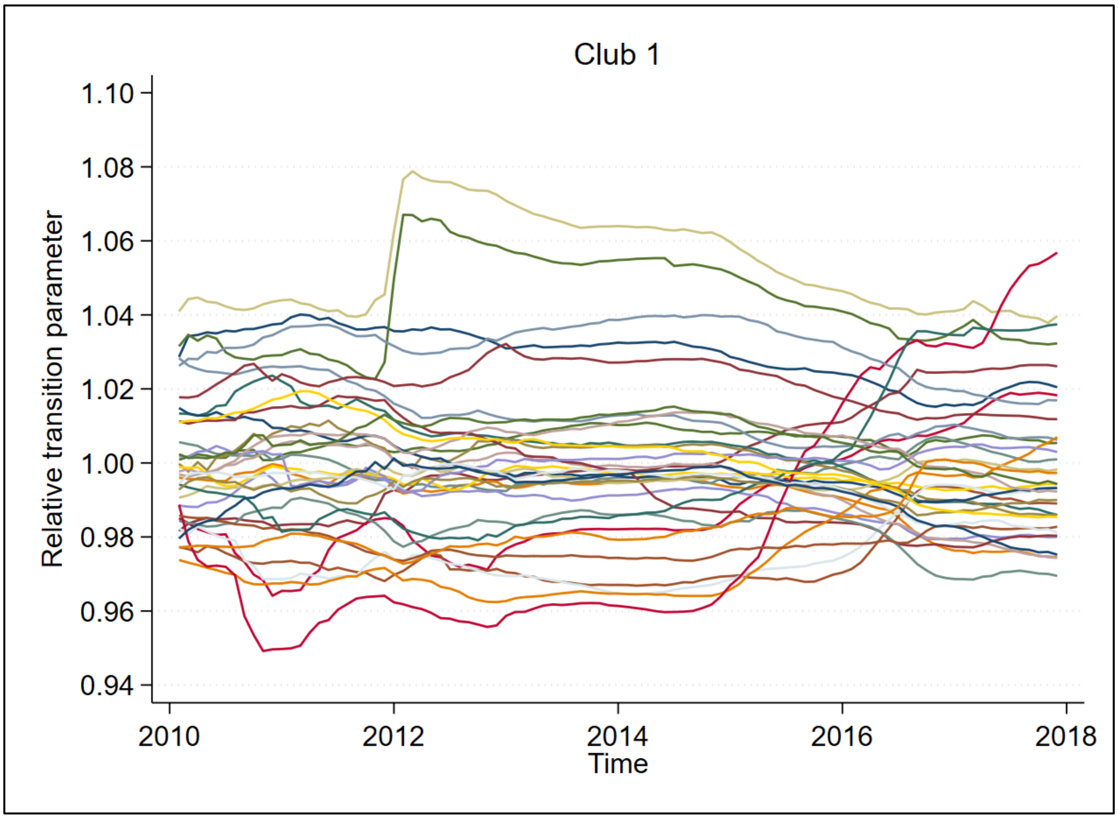
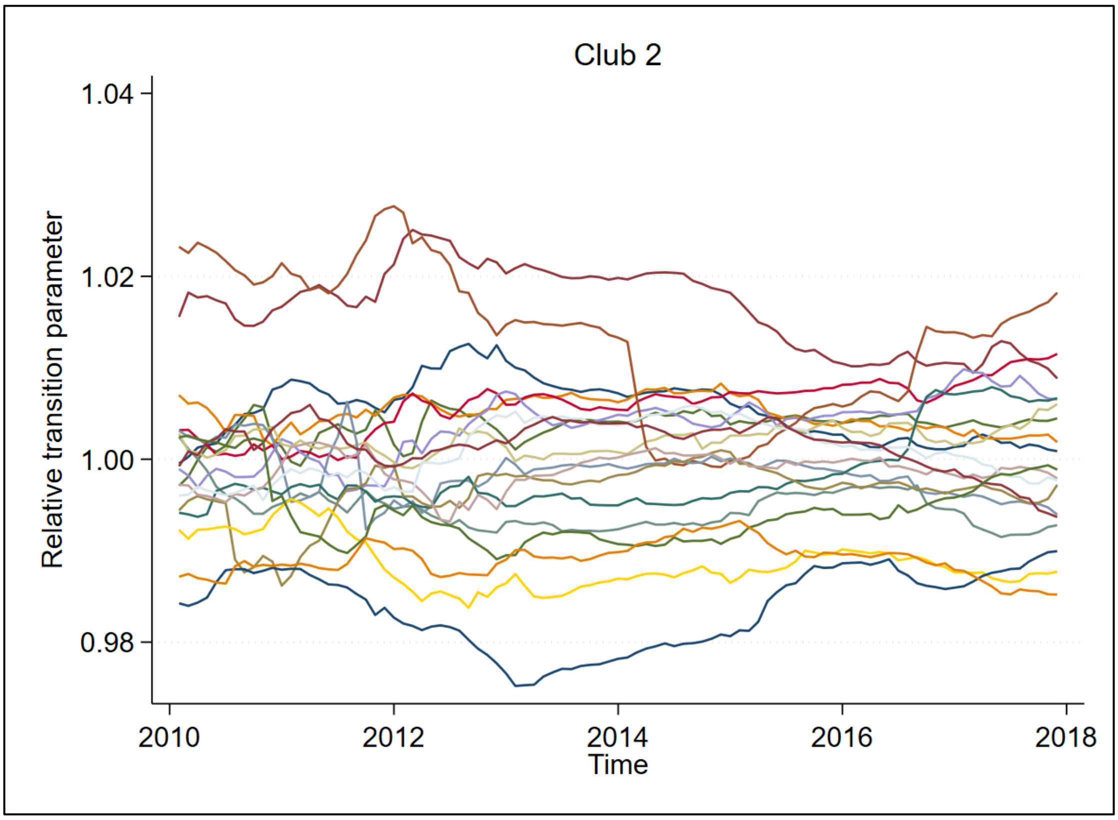


Figure 5.5 Relative transition paths of the final clubs for China's 70 cities, February 2010–December 2017

The relative transition paths of cities per club are shown in Figure 5.6. The housing price dispersion per club seems to be temporally stable. Compared with cities in Club 4, the cities in Clubs 1–3 show convergence within their respective clubs. Also, we found that the transition mainly took place in the period January 2012–October 2015, while the curves have remained stable and not shrunk since January 2016.


Club 1
1.10
1.08
1.06
1.04
1.02
1.00
0.98
0.96
0.94
Relative transition parameter
2010
2012
2014
2016
2018
Time


Club 2
1.04
1.02
1.00
0.98
Relative transition parameter
2010
2012
2014
2016
2018
Time

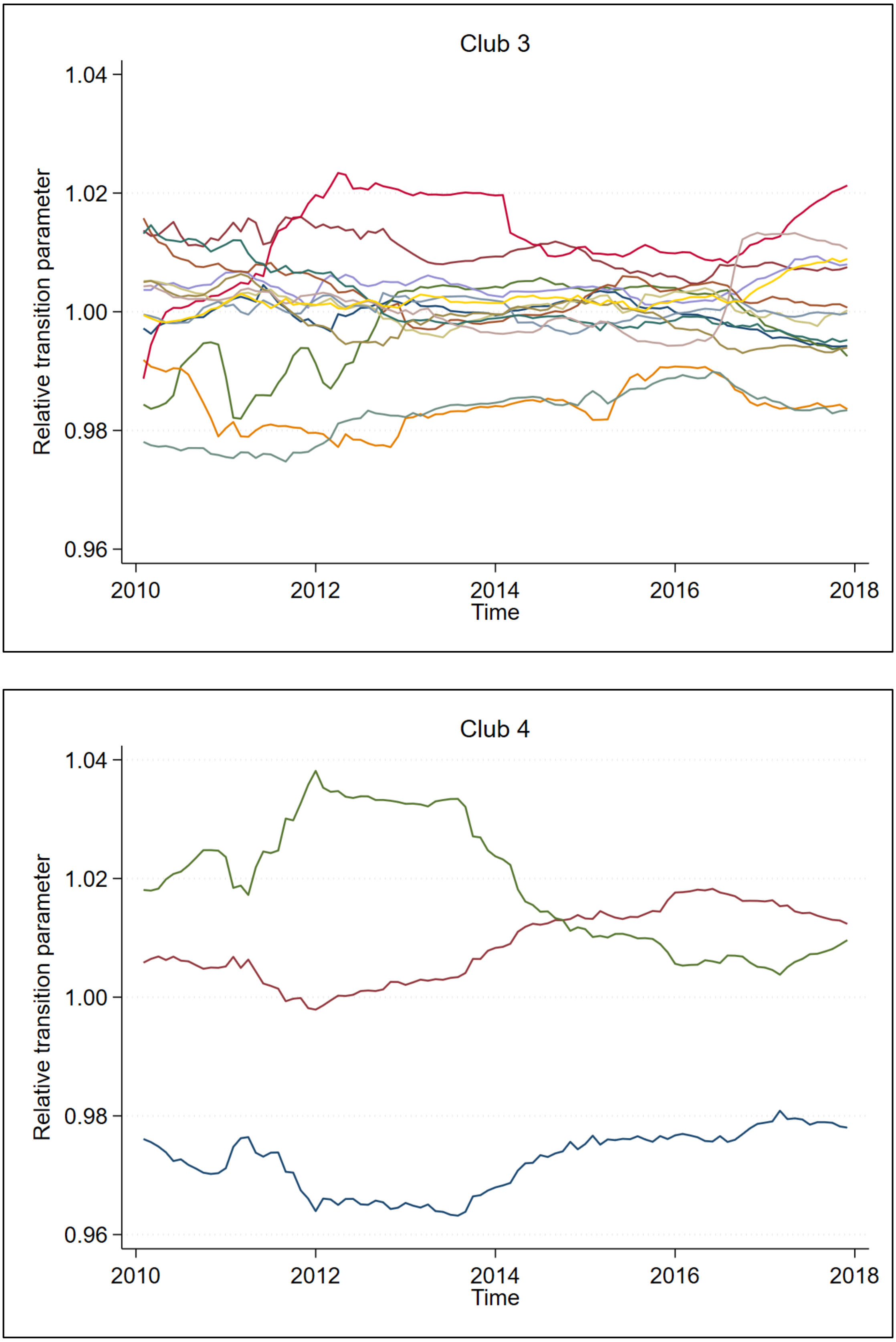


Figure 5.6 Relative transition paths of China's 70 cities by clubs, February 2010 - December 2017

We found some evidence of conditional β-convergence within each club. Figure 5.6 shows that cities with low housing prices have a high growth rate, catching up with the high-priced cities. An OLS regression was further used to analyze the difference between the log price indices in 2010 and 2017 while controlling for GDP, income, land price, and population size. The coefficients in Table 5.3 confirm conditional β-convergence (Young et al., 2008). In Clubs 1 and 3, the coefficients are -0.398 and -0.471, respectively, and are statistically significant at the 95% level. In Club 2, the coefficients are marginally significant (90% level). According to the relative transition path of each city per club, the members in each club show heterogeneous dynamics along with converging to a different steady state.

Table 5.3 The conditional β-convergence test of the finial club based on OLS

Club	Coef.	*t*-stat.	*p*-value
1	-0.398	-2.72	0.011
2	-0.186	-1.68	0.111
3	-0.471	-2.60	0.023
4	-0.119	-0.56	0.673

5.4.3 Drivers of club convergence of regional housing prices

The above results indicate that regional housing prices form several subgroups of convergence, which implies that China's housing market faces striking heterogeneity at the regional level. Next, we explored the potential factors determining the club membership of regional housing prices.

Depending on the ordinal nature of our dependent variables, ordered logit models were formulated and fitted with maximum likelihood estimation (McKelvey & Zavoina, 1975), as Equation (10) shows,

$$y_i^* = X_i\beta + \varepsilon_i \qquad (10)$$

Although y_i^* is unobservable, it has following thresholds: $y_i = j$ *if* $r_{j-1} < y_i^* \leq r_j$. Thus, the latent ordinal variable y_i^* denotes club j (J = 1, …, J) to which city i belongs, and a club's rank is in a logistic way based on the mean housing prices index. Here, with the final club as the response variable, we take value 4 for cities in Club 1, value 3 for cities in Club 2, value 2 for cities in Club 3, and value 1 for cities in Club 4. The explanatory variables X_i are the potential drivers of club formation for city i (i = 1, …, N). The column vector $\boldsymbol{\beta}$ indicates the estimated coefficients. The error term ε_i has a logistic distribution.

The probability that city i belongs to club j is:

$$p_{ij} = p(y_i = j) = p(r_{j-1} < y_i^* \leq r_j) = F(r_j - X_i\beta) - F(r_{j-1} - X_i\beta) \qquad (11)$$

Where F is a logit cumulative distribution function $F(z) = \frac{e^z}{1+e^z}$. The predicted probability is evaluated for the averages of all remaining variables, and the probability value is a positive correlation with the corresponding club's size and negative correlation with the distance to the sample mean.

Additionally, the marginal effect of the predicted probability is examined to assess the importance of the variables X_i for the club membership,

$$\frac{\delta p_{ij}}{\delta X_{ni}} = \left\{F'(r_j - X_i\beta) - F'(r_{j-1} - X_i\beta)\right\}\beta_n \qquad (12)$$

one unit of change in a variable X_i changes the probability of city i belonging to club j by the marginal effect expressed as a percentage.

Based on the empirical literature on the determinants of regional housing price behavior, the dynamic changes in housing prices are closely related to socioeconomic and demographic factors, housing market features, urban amenities, and geographical elements (Blanco et al., 2016; Holmes et al., 2019; Zhang & Fan, 2019). Considering the accessibility of data, we set the explanatory variables X_i from the above four aspects to identify possible relevant factors for convergence club formation in housing prices. All explanatory variables considered in the model were measured based on the average values during the chosen period. Table 5.4 shows the detailed data definition and source.

Table 5.4 Variables definition and sources

Variable	Mean	Definition	Source
Geographic factors			
Geographical division	2.314	Based on economic development level across regions: Setting 1/2/3= western /central/ eastern cities, respectively	China Ministry of Public Works
City tier	2.714	Based on Chinese urban hierarchy division: Setting 1/2/3/4/5= the 4^{th}-/3^{rd}-/2^{nd}-/new 1^{st}-/1^{st}-tier cities, respectively	China Business Network
Coast	0.171	Dummy variable: 1 = coastal cities and 0 = otherwise	China Ministry of Public Works
Socioeconomic factors			
Ln GDP	7.631	The annual real GDP per capita in logs, 2006–13 average	China City Statistical Yearbook
Ln pop.	6.350	Total resident population in logs, 2010–17 average	China City Statistical Yearbook
Ln Income	9.865	The annual per capita disposable income in logs, 2006–13 average	China City Statistical Yearbook
GDP growth rate	13.20	The annual growth rate (%) of real GDP per capita, 2006–13 average	China City Statistical Yearbook
Pop. growth rate	6.258	The annual growth rate (%) of resident population, 2010–17 average	China City Statistical Yearbook

Income growth rate	1.108	The annual growth rate (%) of per capita disposable income, 2006–13 average	China City Statistical Yearbook
Housing market			
Ln land price	2.687	Land prices for housing in logs, 2009–11 average	China City Statistical Yearbook
Rental market	4.632	Rent prices indices in logs, 2007–09 average	
Housing regulation	1.610	Housing regulation restrictions in five degrees: very strict (40), strict (30), some (20), few (10), no (0) restrictions. Note: based on the number of regulations (i.e., 10 points for each policy between 2010 and 2017).	China Ministry of Public Works
Urban amenity			
Ln education	2.424	The number of urban high schools in logs, 2010–17 average	China City Statistical Yearbook
Ln healthcare	5.325	The number of the general hospitals in logs, 2010–17 average	China City Statistical Yearbook
Landscape	3.705	The amount of green space (%), 2010–17 average	China City Statistical Yearbook
Ln climate	2.687	The annual average temperature in logs, 2010–17 average	China City Statistical Yearbook

The results of the ordered logit regressions (including the marginal effects) are summarized in Table 5.5. Unlike the insignificant geographic division, city tier is positive and significant. Cities belonging to the higher city-tier have a higher probability of converging to one club with a higher price growth rate one level higher. Similarly, being located along the coast increases the likelihood of belonging to a higher growth rate club one level higher. Except for logged income, GDP growth rate, and population growth rate, the remaining variables of socioeconomic factors were not significant. The significantly negative coefficients of logged income are consistent with the results of Holmes et al. (2019). Even though the GDP growth rate is positive, the variable rarely reaches statistical significance. The estimated parameter of population growth rate is consistently positive and significant, indicating that cities with a higher population growth rate have an increased likelihood of being part of a club with a higher-growth converging level. Concerning housing market factors, the logged land price and rental market are both negative and insignificant. This means that the rental market in China does not affect club membership, unlike the rental market in Spain (Blanco et al., 2016). The estimated parameter of housing regulation is positive and significant, indicating that those cities with tighter housing demand regulation are more likely to be part of a club with a higher-growth converging level. The results show that housing demand regulation plays a key role in club formation, confirming an earlier study by Kim and Rous (2012). The estimated coefficients on education, landscape, and climate are positive but do not reach significance. It is possible that the importance of educational quality and landscape for driving club formation in cities is more important than that between cities (Holmes et al., 2019). As climate conditions are largely similar across China, it is not surprising that climate is not related to the convergence club membership, although thus does contrast with US results (Kim & Rous, 2012). Logged healthcare is statistically significant but negative, meaning that cities with a higher healthcare level are more likely to belong to a club with a lower-growth converging level. Moreover, we fitted an ordered probity model to test the robustness of the drivers of the club formation. The results are given in the supplementary materials (Table A 5.1). The signs of the significant variables are consistent, and the magnitudes of the estimates are comparable. These results confirm the robustness of our findings.

Table 5.5 Estimation results from the ordered logit model

	Parameter estimates				Marginal effects			
					Club 1	Club 2	Club 3	Club 4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Geographic factors								
Geographical division	-0.273	0.481	0.213	-0.582	-0.080	0.016	0.045	0.020
	(0.335)	(0.451)	(0.466)	(0.589)	(0.080)	(0.017)	(0.047)	(0.021)
City tier	0.751***	1.940***	1.417**	1.372*	0.188*	-0.037	-0.105*	-0.047
	(0.249)	(0.545)	(0.687)	(0.753)	(0.100)	(0.029)	(0.056)	(0.032)
Coast	1.074	1.400	2.511**	2.380**	0.327**	-0.064*	-0.182**	-0.081
	(0.833)	(0.879)	(1.073)	(1.076)	(0.133)	(0.035)	(0.088)	(0.049)
Socioeconomic factors								
Ln GDP		0.324	0.488	1.165	0.160	-0.031	-0.089	-0.039
		(0.722)	(0.731)	(0.796)	(0.107)	(0.027)	(0.062)	(0.031)
Ln pop.		-0.954	-0.624	0.0807	0.011	-0.002	-0.006	-0.003
		(0.629)	(0.621)	(0.633)	(0.087)	(0.017)	(0.048)	(0.021)
Ln income		-6.099***	-5.790**	-6.574***	-0.903***	0.177*	0.503***	0.223*
		(2.109)	(2.307)	(2.353)	(0.285)	(0.103)	(0.183)	(0.123)
GDP growth rate		0.320*	0.223	0.120	0.016	-0.003	-0.009	-0.004
		(0.189)	(0.204)	(0.217)	(0.029)	(0.006)	(0.017)	(0.008)
Pop. growth rate		0.144**	0.184**	0.157*	0.022*	-0.004	-0.012*	-0.005
		(0.0710)	(0.0746)	(0.0863)	(0.011)	(0.003)	(0.007)	(0.004)

Income growth rate		27.35	39.61	34.46	4.731	-0.926	-2.636	-1.168
		(22.96)	(25.24)	(26.37)	(3.572)	(0.889)	(1.980)	(1.026)
Housing market								
Ln land price			-0.552	-0.316	-0.043	0.009	0.024	0.011
			(0.538)	(0.585)	(0.080)	(0.016)	(0.045)	(0.020)
Rental market			-13.18	-18.79	-2.580	0.505	1.438	0.637
			(11.33)	(12.27)	(1.658)	(0.399)	(1.011)	(0.463)
Housing regulation			0.578^{*}	0.643^{*}	0.088^{**}	-0.017^{*}	-0.049^{*}	-0.022^{*}
			(0.313)	(0.330)	(0.041)	(0.009)	(0.027)	(0.015)
Urban amenity								
Ln education				0.0398	0.005	-0.001	-0.003	-0.001
				(0.327)	(0.045)	(0.009)	(0.025)	(0.011)
Ln healthcare				-1.993^{**}	-0.274^{***}	0.054	0.152^{**}	0.068^{*}
				(0.816)	(0.103)	(0.033)	(0.066)	(0.038)
Landscape				0.918	0.126	-0.025	-0.070	-0.031
				(3.258)	(0.444)	(0.087)	(0.248)	(0.112)
Ln climate				0.0775	0.011	-0.002	-0.006	-0.003
				(0.932)	(0.128)	(0.025)	(0.071)	(0.032)
Pseudo R^2	0.083	0.216	0.250	0.294				
Wald (p-value)	13.52	35.13	40.58	47.83				
	(0.00)	(0.00)	(0.00)	(0.00)				

Notes: $N = 70$. Columns (1)–(4) report parameter estimates. Columns (5)–(8) report marginal effects calculated at mean values for the estimated model (4). The regression includes a constant term and robust standard errors in parenthesis. Statistical significance is indicated by *** at 1%, **at 5%, *at 10%.

To further account for the role of the independent variables in the likelihood of cities belonging to a specific club, columns 5–8 in Table 5.5 present the corresponding marginal effects calculated at the average of the independent variables from the model in column (4). Those factors have a pronounced effect on Club 1 convergence in relative terms. The results show that disposable income per capita (Ln Income) has the largest impact on driving club membership. A one-unit increase in the average annual disposable income per capita decreases the likelihood of belonging to Club 1 by 90.3 percent, but increases the likelihood of being in Clubs 2, 3, and 4 by 17.7, 50.3, and 22.3 percent, respectively. Like previous studies (Blanco et al., 2016; Kim & Rous, 2012), we found that the variables coastal city and the growth rate of population indeed play a key role in club formation. A coastal city increases the probability of belonging to Club 1 by 32.7 percent and decreases the probability of belonging to Clubs 2, 3, and 4 by 6.4, 18.2, and 8.1 percent, respectively. A one-point increase in the average annual growth rate of resident population increases the likelihood of belonging to Club 1 by 2.2 percent and reduces the likelihood of being in Club 3 by 1.2 percent, but has no significant influence on the probability of being in Club 2 or 4. As for city tier, a city belonging to a city tier one tier higher does not have a significant influence on the probability of being in Club 2 or 4, but does increase the probability of being in Club 1 (by 18.8 percent) and reduces the probability of being in Club 3 (by 10.5 percent). Regarding housing regulation, a one-point increase in housing purchase regulation increases the probability of belonging to Club 1 by 8.8 percent and decreases the probability of belonging to Clubs 2, 3 and 4 by 1.7, 4.9 and 2.2 percent, respectively. Lastly, the marginal effect of healthcare shows that a one-unit increase in log hospital decreases the probability of being in Club 1 by 27.4 percent, but increases the probability of belonging to Clubs 3 and 4 by 15.2 and 6.8 percent, respectively.

5.5 Discussion and conclusions

Despite recent efforts to reduce disparity and boost convergence in China's housing market, previous empirical evidence did not confirm the existence of overall convergence. We therefore investigated a new form of club convergence in regional housing prices among China's 70 major cities using monthly housing prices indices over 12 years, providing another explanation for the existing findings on regional housing price convergence in China (Liu et al., 2018; Mao, 2016; Zhang & Morley, 2014). The main contribution of this study is that it applied a non-linear model (i.e., log t test) that avoided endogenously clustered regions. It also contributed by assessing the factors driving club formation.

The empirical results on club convergence suggest that regional housing prices show heterogeneous dynamics across Chinese cities and identify four convergence clubs with converging housing prices. This implies that the regional housing market is to some degree segmented, corresponding with the current situation of the national housing market. The developed cities mostly converge to the club with a high growth rate, the converging speed of which is slower than that of the cities in the other clubs. Second, we found no evidence that club members are clustered across China, although our derived club formation is not entirely compatible with the traditional city tier and geographical division in China. Cities' convergence dynamics in each club differ according to their relative transition path, but we found conditional β-convergence within Clubs 1–3 (but not Club 4).

Our analysis of the drivers of club formation favors the club convergence hypothesis, highlighting the role of the mean conditions in the final club formation. Specifically, in line with results reported elsewhere (Blanco et al., 2016; Holmes et al., 2019; Kim & Rous, 2012), our findings from the ordered logit regression indicate that disposable income per capita, the growth rate of the resident population, and housing regulation play a significant role in driving club formation in China's regional housing prices. We also found that city tier and healthcare influence membership of regional housing price clubs.

The formation of different groups of regional housing prices reflects differences in socioeconomic, housing market, geographical, and urban amenity conditions. In other words, the different growth paths of housing prices in China regions are mainly caused by differences in population growth, housing regulations, healthcare level, and belonging to different city tiers.

Given that the real estate market is still one key pillar of economic growth in China and that the regional housing price dynamic is a barometer for housing market and even regional balance, our findings have certain policy implications. The disparities in housing prices across regions may increase growth inequalities. Thus, narrowing the disparities in incomes, population growth, housing regulations, urban hierarchies, and urban healthcare would help to reduce the disparities in regional housing prices and promote convergence. Yet, because the clubs are sensitive to the factors to different degrees, these measures would not have the same effect for different regions. Thus, policymakers should take differentiated and targeted measures in order to effectively reduce the imbalance and avoid ineffective and costly "one-size-fits-all" policy.

5.6 Appendix

Table A 5.1 Estimation results from the ordered probit model for robustness

	Parameter estimates				Marginal effects			
					Club 1	Club 2	Club 3	Club 4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Geographic factors								
Geographical division	-0.157	0.279	0.148	-0.302	0.0183	0.0426	0.0126	-0.0735
	(0.199)	(0.262)	(0.272)	(0.343)	(0.0213)	(0.0497)	(0.0149)	(0.0826)
City tier	0.434***	1.139***	0.851**	0.749*	-0.0453	-0.106*	-0.0314	0.182*
	(0.142)	(0.309)	(0.393)	(0.430)	(0.0310)	(0.0603)	(0.0261)	(0.103)
Coast	0.400	0.675	1.251**	1.264**	-0.0764*	-0.178**	-0.0529*	0.307**
	(0.440)	(0.481)	(0.562)	(0.575)	(0.0463)	(0.0853)	(0.0301)	(0.129)
Socioeconomic factors								
Ln GDP		0.140	0.288	0.689	-0.0417	-0.0972	-0.0289	0.168
		(0.400)	(0.423)	(0.475)	(0.0325)	(0.0676)	(0.0248)	(0.113)
Ln pop.		-0.512	-0.385	-0.0184	0.00111	0.00260	0.000772	-0.00449

	(0.327)	(0.352)	(0.393)	(0.0238)	(0.0554)	(0.0165)	(0.0957)
Ln income	-3.528***	-3.438**	-3.822***	0.231*	0.539***	0.160	-0.930***
	(1.219)	(1.351)	(1.405)	(0.125)	(0.197)	(0.0973)	(0.307)
GDP growth rate	0.198*	0.132	0.0786	-0.00475	-0.0111	-0.00329	0.0191
	(0.111)	(0.121)	(0.129)	(0.00821)	(0.0182)	(0.00513)	(0.0310)
Pop. growth rate	0.0828**	0.111***	0.0913*	-0.00552	-0.0129*	-0.00382	0.0222**
	(0.0389)	(0.0421)	(0.0482)	(0.00355)	(0.00697)	(0.00274)	(0.0112)
Income growth rate	16.09	23.44*	18.90	-1.142	-2.665	-0.791	4.598
	(12.79)	(13.69)	(14.64)	(0.985)	(2.066)	(0.758)	(3.522)
Housing market							
Ln land price		-0.334	-0.201	0.0122	0.0284	0.00842	-0.0489
		(0.315)	(0.344)	(0.0213)	(0.0487)	(0.0150)	(0.0834)
Rental market		-9.137	-12.86*	0.777	1.813*	0.538	-3.128*
		(6.614)	(7.242)	(0.494)	(1.086)	(0.401)	(1.713)
Housing regulation		0.311*	0.351*	-0.0212	-0.0495*	-0.0147*	0.0854**
		(0.181)	(0.188)	(0.0145)	(0.0273)	(0.00857)	(0.0423)

Urban amenity								
Ln education				0.0792	-0.00478	-0.0112	-0.00331	0.0193
				(0.196)	(0.0121)	(0.0278)	(0.00811)	(0.0476)
Ln healthcare				-1.068**	0.0645*	0.151**	0.0447	-0.260**
				(0.461)	(0.0362)	(0.0691)	(0.0284)	(0.106)
Landscape				-0.0343	0.00207	0.00484	0.00144	-0.00835
				(1.807)	(0.109)	(0.255)	(0.0757)	(0.440)
Ln climate				0.142	-0.00856	-0.0200	-0.00593	0.0344
				(0.552)	(0.0337)	(0.0778)	(0.0228)	(0.134)
Pseudo R^2	0.0759	0.2168	0.2503	0.2875				
Wald (p-value)	12.23	34.94	40.33	46.33				
	(0.00)	(0.00)	(0.00)	(0.00)				

Notes: N = 70. Columns (1)–(4) report parameter estimates. Columns (5)–(8) report marginal effects calculated at mean values for the estimated model (4). The regression includes a constant term and robust standard errors in parenthesis. Statistical significance is indicated by *** at 1%, ** at 5%, * at 10%.

Chapter 6 Summary and Conclusions

Cities offer the physical space for human activities and the growth of cities is tightly connected to urban residents' welfare. The overall research aim of this thesis was to investigate how urban growth relates to residents' welfare in China. This concluding chapter reviews the main findings and reflects upon their implications for research and policy.

6.1 Main findings

The introduction of this thesis presented an overarching research question:

What do housing market dynamics reveal about the relationship between urban growth and resident welfare in China?

Several general points can be highlighted as tentative answers to this broad research question. Generally, our research findings for China support the notion that, from a spatial point of view, urban growth has both positive and negative consequences for residents' welfare.

Firstly, the uneven distribution of urban characteristics segments urban welfare in space and is well captured with housing prices. Under the theoretical framework of the hedonic pricing model, the spatial distribution of housing prices revealed the spatial disparity of urban welfare within cities in Chapters 2-4. Chapter 5 demonstrated how socioeconomic welfare differed across cities too. This result was obtained by combining regional housing price convergence with the regional convergence analysis approach. The general finding that a spatial inequality of urban growth is associated with uneven residents' welfare resonates with similar findings in the literature (e.g., Ballas (2021); Ala-Mantila et al. (2018)).

Secondly, welfare effects for urban residents can be positive or negative, and even both at the same time. We have shown in Chapter 2 that proximity to the Asian phenomenon of wet markets has a nonlinear influence on residents' welfare. That is, as distance to wet markets increases, the negative influence gradually declines and changes to positive beyond a certain threshold. The underlying mechanism is that the overall welfare benefit of their quality outweighs their accessibility. Chapter 3 demonstrated that air pollution in Beijing had a negative association with residents' welfare, and the pollution was worse in the inner city than in the suburbs. Regarding regional integration policy in Chapter 4, we have shown the significantly positive external effect on urban living conditions on the periphery of a core city, especially in areas where two cities border on each other. Lastly, club convergence of regional housing prices in Chapter 5 indicated the structural spatial inequality of residents' welfare across regions. The empirical research provided evidence from China's cities on the universal law that cities are complex systems of cities with non-linear effects on the lives of its citizens (Glaeser, 2011a; Johnson & Munshi-South, 2017).

Thirdly, our analyses revealed that specific urban features might affect residents' welfare across multiple dimensions simultaneously. Based on their quantity and quality, the wet markets in Chapter 2 played a twofold role in residents' welfare, with both social and environmental aspects. Their accessibility had a nonlinear effect on residents' welfare since the harm to their environmental welfare progressively offset the service benefit of social welfare. In Chapter 3, air pollution represented a negative externality on urban residents' quality of life, and also bothered residents' daily lives in society. The integration policy of inter-cities contributed to improving the living conditions of residents in a city on the periphery of a core city, which enhanced social welfare as well. Next, the convergence dynamics of regional housing prices obviously reflected socioeconomic inequality, including the cost of living and economic development, showing the divides in socio-economic welfare across regions. In fact, cities simultaneously exhibit multiple aspects of urban welfare (Kyttä et al., 2016).

Fourthly, urban features at a higher spatial scale influence the welfare of urban residents via a lower spatial scale channel. This is particularly evident when taking housing markets to measure the welfare implications of urban growth. In Chapter 4, regional integration benefitted inhabitants thanks to investments in cross-border transit, such as a light rail system, a new highway, and new urban areas with high-quality facilities within the city. Furthermore, an examination of the factors underlying club convergence of regional housing prices in Chapter 5 found that the city's healthcare level was a significant driver for convergence club formation. In summary, urban growth relates to the welfare of citizens at different scales. These findings align with those of Mimar et al. (2022). The patterns are useful to understand since they also reflect citizens' residential choices and trade-offs between wages, the cost of living and the quality of life in space (Roback, 1982).

6.2 Research implications

This thesis's findings have several implications for research, as elaborated below.

One of the key contributions of this research to current knowledge is its examination of the link between urban growth and residents' welfare in the Chinese context. Unlike most Western developed countries such as Europe and the U.S. which experienced orderly urbanization in the 19th century, Chinese cities currently face the tension between fast urbanization and planning (Chu, 2020). The context is characterized by different paths and stages of urban growth than for those observed in developed western countries (Randolph & Storper, 2022). Nonetheless, the evidence presented in this thesis regarding China's experience supports the pervasive point that urban growth does both benefit and challenge residents (Glaeser, 2011a; Seto et al., 2010), similar to historical and contemporary evidence in developed countries (Glaeser & Kahn, 2010; Glaeser & Shapiro, 2003; Rodríguez-Pose & Storper, 2020).

Secondly, the primary research question of the thesis concerns the perspective of spatial inequality across multiple dimensions and scales. In accordance with prior research that has focused on a single dimension and scale, this thesis's results, overall, indicate that urban characteristics do matter in shaping residents' quality of life in space. This is consistent with the arguments put forth by Florida et al. (2013), and aligns with the findings of Bernini and Tampieri (2019) in their study of Italy. Importantly, this thesis underscores the significance of spatial inequality in urban contexts for residents' welfare, corroborating the conclusion drawn by Ballas (2021) on the topic of happiness and the discussion by Ala-Mantila et al. (2018) on wellbeing in their work.

In detail, drawing upon prior research (Chay & Greenstone, 2005; Deaton, 2008; Pope & Pope, 2015), I examined the broad dimensions of urban welfare in socio-economic and environmental domains with respect to urban characteristics in China. My findings suggest that environmental pollution, particularly air pollution, remains a serious challenge that threatens the welfare of urban residents in China, as well as in other emerging economies such as India (Grover & Singh, 2020), and even some developed countries (Hitaj et al., 2018; Le Boennec & Salladarré, 2017). Additionally, my research underscores the significance of policy interventions in improving residents' quality of life, as demonstrated in Chapter 4 where we analyzed the external effects of regional integration on urban welfare. My results thus suggest that urban planning and policies play a crucial role in enhancing residents' lives, consistent with the argument put forth by Kleinert and Horton (2016).

Thirdly, my research reveals that the relationship between urban growth and residents' welfare differs across income groups. In effect, the welfare effect of urban growth on residents is not evenly distributed among individuals (Buitelaar et al., 2017). The spatial disparity in housing prices highlighted in our findings suggests a link between income inequality and spatial segregation (Glaeser et al., 2009; Ham et al., 2021). Moreover, the findings imply that high-income residents are more likely to enjoy greater welfare benefits than low-income residents (Sun, Fu, et al., 2017), given that the spatial distribution of urban facilities and services reflects income differences in space (Roback, 1982). Specifically, the evidence presented in Chapters 2 and 3 indicates that high-income residents are more willing to pay a premium for high-quality urban amenities and natural environment amenities compared to low-income ones. These results align with previous research showing that low-income residents experience welfare loss due to urban growth inequality in the Netherlands (Buitelaar et al., 2017).

Fourthly, my research suggests that the welfare impact of specific urban features on residents may shift over time. Evaluating the impact of specific urban characteristics is a challenging task (Greiling, 2006). The effect of urban welfare can change over time, making a simplistic analysis of examining static average values inadequate for a realistic understanding (Hitaj et al., 2018; Shaw, 2021). In particular, Chapter 3 revealed that the effect of air pollution changes over time, while Chapter 4 showed the positive effect of the earlier measures within regional integration policy diminishes as other subsequent measures are implemented. These findings demonstrate the dynamic nature of complex urban features and their interaction with human activities (Johnson & Munshi-South, 2017).

The *fifth* implication of my research concerns the crucial role that housing markets play. Measuring urban welfare for residents under multiple dimensions and scales is a challenging task, and despite recent efforts, such as Mimar et al. (2022)'s analysis of urban welfare at the intercity level with mobility networks, it remains difficult to separate different dimensions and constraints at various research scales. However, housing has numerous social, wealth, and economic aspects that are directly related to the welfare of city dwellers, given its well-known special characteristics, such as dwellings, consumption, and investments (Ronald & Dewilde, 2017). Thus, my research sheds light on the welfare effect of urban growth through the housing market, based on the relationship between the housing market, urban growth, and residents' welfare.

Lastly, by combining administrative data sources and big urban data sources, I was able to provide a more nuanced and insightful understanding of the complex urban processes and their impact on residents' welfare, together with advanced measurements and econometrics. Big urban data indeed provide a broader and finer record of urban life over time and space, enabling the timely exploration of urban processes (Glaeser et al., 2018). The use of advanced measurement techniques, such as spatial econometric models also improved the robustness of the research results. Particularly, instead of the conventional questionnaire survey (Qi et al., 2019) and general OLS model, in Chapter 2 we adopted a spatial regression model and captured the subject perception of consumers for the quality of urban amenities, with site rating data. The use of big urban data, encompassing social media data, has proven to be advantageous in enhancing the quality of urban services through the acquisition of more precise information, and facilitates more sophisticated urban modelling and analysis (Lin & Geertman, 2019).

6.3 Policy implications

Cities do bring positive and negative effects on the lives of their residents. Governments should be responsible for looking for efficient solutions to handling urban challenges and making them more pleasurable and livable (Glaeser, 2011a). It is important to untangle the intrinsic relationship between urban growth and residents' welfare. As such, the spatial patterns and the interplay of urban features and residents' welfare have been studied at various dimensions and scalars in this PhD thesis. In light of the analyses presented in the previous chapters, four broad policy implications can be drawn.

Firstly, urban development and planning in Chinese cities has historically prioritized economic growth, during the early to mid- stage of the urbanization process (Zhang et al., 2022). The welfare of urban residents has been given less attention to and has not been refined from various dimensions and scales (Brockmann et al., 2009; Wu, 2015). Despite this, an increasing number of scholars have emphasized that cities should be designed for people and places rather than solely for profit (Brenner et al., 2012; Gehl, 2013), and suggested that urbanism should be guided by residents' needs for satisfaction (Caprotti, 2018; Cardoso et al., 2022). This thesis argues that urban-planners and policymakers need to recognize the importance of urban growth in meeting the needs of residents from multiple dimensions and spatial scales. They should consider how to plan cities and improve residents' quality of life effectively. For instance, the empirical findings presented in Chapters 2-5 indicate that cities will be more livable if public services are equitable, the air is clean, and the cost of living is affordable.

Secondly, a variety of urban physical facilities are being constructed in Chinese cities to accommodate fast urban expansion and serve society, with government regulation (Chu, 2020). Yet, their efficiency is generally neglected from a spatial perspective (Wei et al., 2017). In effect, the spatial planning and management of cities are strongly linked to residents' welfare (Kleinert & Horton, 2016), Our findings indicate that the spatial inequality of urban features including urban amenities, air quality, and housing, segments urban welfare in space, thereby reducing the overall effect of urban welfare. Caldarice (2018, p. 15) states that "A functioning city promotes the delivery of urban facilities, simplifying access to them, enabling them to be placed on sites that are appropriate, qualified, pleasant, and comfortable for all users". As such, we should build or upgrade urban elements with a kind of logic that can satisfy the needs of citizens and guarantee a higher level of satisfaction with the quality and quantity of urban services and facilities given in cities.

Thirdly, specifically, my findings demonstrate the diversity in how different urban characteristics affect residents' welfare. For instance, Chapter 2 examined the amenity and dis-amenity effect of urban service accessibility and its subjective perceived effect, while Chapter 3 analyzed the dynamic changes in the welfare consequences of air quality. Evaluating the effectiveness of urban services is complex due to the relationship between urban growth and residents' welfare. Therefore, assessing the welfare value of urban features requires taking into account various measured indicators, their short- or long-term effects, and their specific properties and relationships with residents' needs (Durand, 2015). Moreover, it is essential to note that urban planning and management should be reasonable and scientific to avoid potential dis-amenity effects on residents' lives, as suggested in Chapter 2. Urban planners and policymakers should carefully consider the potential impacts of urban development on residents' welfare and aim to improve the overall quality of life in the city.

Fourthly, the heterogenous effects of urban growth on residents' welfare across income are significant. In China, mostly of urban welfare plans have been designed with a focus on settled or theoretical residents of major cities, without taking into account the specific demands of certain user groups, such as high-income individuals or residents of small communities (Wu, 2015). However, policymakers should develop regulations based on the specific demands of different income groups to ensure equitable distribution of urban welfare (Ludwig et al., 2012). As I have demonstrated in the thesis, high-income individuals prioritize the quality of urban facilities and the natural environment, whereas low-income individuals have limited access to urban welfare due to economic inequality as Buitelaar et al. (2017)state. Therefore, we must be aware of the potential loss of urban welfare for low-income individuals and provide specific care to compensate for this loss in urban inequality.

Finally, an overarching insight that emerges from this thesis is the crucial role played by the housing market in connecting urban growth and residents' welfare. Spatial inequalities in urban services and infrastructure distinguish the welfare of the affluent and poor through residential choices, and housing prices at the regional level project the regional cost of living. Thus, in my view, properly controlling and coordinating the housing market is crucial for ensuring residents' welfare, in the era of overheated property market investment in China (Glaeser et al., 2017). In addition to improving the provision of urban facilities, governments can implement targeted housing policies that draw upon related housing regulations from Western countries, such as social welfare and rental housing, property tax reform, and others, to narrow the welfare and wealth gap across income and city groups and eliminate disparities (Glaeser & Gyourko, 2018; Ronald & Dewilde, 2017), given the immature and incomplete regulations in China's housing market.

6.4 Limitations and future research

Finally, I discuss the key limitations of this thesis and how these limitations prompt avenues for further research.

Theoretical issues

I will briefly discuss two key theoretical limitations of this thesis, both of which relate to the hedonic pricing model. Firstly, the hedonic price theory used in the initial phase of the study is based on a *static* spatial equilibrium model, which does not account for labor flows at the inter- and intra-city level (Rosen, 1974). However, workers often move between regions to optimize their welfare, considering factors such as the cost of living, wages, and other urban amenities (Diamond, 2016; Glaeser et al., 2014). Thus, residential location choices are influenced by a trade-off between these factors. In this case, it is essential to consider a dynamic spatial equilibrium model with cross-regional labor mobility when exploring the relationship between urban growth and residents' welfare. In fact, I am currently working to apply such a framework to the topic of disentangling the relationship between urban innovation and housing prices through human capital flows.

Secondly, the hedonic price model has traditionally been limited in its ability to evaluate non-market goods or services. Although the hedonic price model is widely used to measure the welfare effect of urban facilities, particularly those that are objectively valued by accessibility and/or proximity, it may not be feasible to meaningfully value certain factors that are subjectively perceived by humans, such as the natural environment or consumption amenities (Kask & Maani, 1992; Kuang, 2017). To obtain more precise results, it is possible to combine objective measures for quantity with subjective measures based on surveys or online ratings that include scores or comments. Chapter 2 presented an analogous case that captures the subjectively perceived effect, utilizing the big data of online review scores. For the possible extensions in future research, it would be analytically advantageous to evaluate the value of certain latent urban amenities connected with the quality of life. For instance, examining the value of urban parks with respect to both their quantity (proximity or accessibility) and their quality (online ratings) would provide a better analytical perspective.

Urban characteristics as research objects

In this thesis, I have examined several key dimensions of urban features that we consider to be important. While I focused on a specific example for each dimension, there are many other features that could have been analyzed, such as supermarkets, wages, urban noise, and urban renewal strategies, which may also have an impact on urban residents' lives. Fortunately, the methods I employed can be readily applied to other empirical contexts. For example, one could investigate the spatial dynamics of housing prices in relation to proximity to supermarkets. Conceptually, a similar framework as in Chapter 2 could be used, and empirically, social media information on residents' experiences with supermarkets could be exploited.

Research design

In this thesis, I explored the relationship between urban growth and residents' welfare across multiple dimensions and scales. In each chapter, the analysis focused on one or two of the dimensions, but not all, and on a single scale. To conduct more encompassing analyses in future research, urban features could be separated into a hierarchical or nested structure of spatial scales, and hierarchical linear modelling (HLM) could be used to explore the relationship between urban growth and residents' welfare (Hu et al., 2022; Lu et al., 2023), For example, one could investigate the welfare effects of urban features at both community and city levels.

In addition, while my analysis focused on the urban welfare effects, I have not yet zoomed in on the heterogeneous welfare effects for individuals differentiated by age, gender, race, and other characteristics. The only exception is the welfare effect across income groups, which was discussed in Chapters 2 and 3 under the assumption that individuals with high incomes generally live in high-priced housing. Moving forward, future research should delve deeper into uncovering the individual heterogeneity for the welfare effects of urban growth across individual characteristics (Neira et al., 2018). For example, one could test whether the welfare effect of the wet market differs for males and females, the older or the young, or the married or unmarried. With the accessibility of data, there is great potential to explore these topics and better understand the diverse welfare effects of urban growth on different individuals.

Within and Beyond China

Lastly, it is important to note that this thesis focused solely on Chinese cities and may not necessarily apply to other regions or cities in China. Different Chinese regions and cities vary in terms of development level, size and structure of the city, environmental quality, availability of public goods or other facilities, implemented planning policies, resident income level, and other contextual features (Yep et al., 2019). For example, air pollution in northern cities such as Beijing is substantially worse than in southern cities such as Shanghai, which means that the consequences of air quality in the two main cities cannot be directly compared (Xu et al., 2019). Therefore, caution should be taken when generalizing our findings to other areas of China. To validate our findings, future research should replicate our work in other Chinese cities to determine if the results hold across different contexts. Such replication work would help to further elucidate the extent to which our findings can be generalized beyond the specific Chinese cities examined in this thesis.

My original research aim was to explore the relationship between urban growth and residents' welfare in emerging and developing countries, with a particular focus on China. My research was primarily concerned with the specific elements of urban growth in China during the urbanization process (Chu, 2020; Guan et al., 2018). For countries or regions with similar circumstances of urban growth and economic development, such as India (Sharma & Abhay, 2022), I recommend further testing the applicability of my findings and resulting policies pertaining to urban growth and residents' welfare. It would also be valuable to compare and discuss the possible differences across these areas. Comparative research could help to identify similarities and differences in the relationships between urban growth and residents' welfare across different regions and provide insights into how policies can be tailored to specific contexts.

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Summary

The link between cities and welfare is hotly debated in economic geography, regional/urban economics, and other related disciplines. Questions concerning the link between urban growth and urban residents' welfare abound due to the complex way in which urban growth and residents' activities interact, and all the more so in cities of emerging countries with rapid urbanization. Taking China as an example, this thesis investigates how urban growth influences urban residents' welfare with the help of housing market dynamics.

This research theme is further elaborated from four research angles. First, how do urban amenities and dis-amenities – united, in our case, in wet markets influence residents' welfare as measured through housing prices? To what extent are there differences in these influences between high- and low-income residents? Second, what is the effect of air quality on residents' welfare within the city? Third, how do urban housing prices change in the context of regional integration policy? How do integration policies affect urban housing prices at different stages of integration? Fourth, is there club convergence of regional housing prices in China's cities? If so, what kinds of urban factors are the potential drivers?

The main contents of each chapter can be summarized as follows.

Chapter 1 presents the research motivation, sketches the background of urban growth in China, and discusses research questions and research approaches.

Chapter 2 explores the welfare effect of urban amenities in their social and environmental dimensions at the intra-city level. By employing data on Beijing housing transactions in 2019 and online review scores of wet markets, we explore both the amenity and dis-amenity effects of such markets and capture objective and subjective perspectives. Our results indicate a nonlinear relationship between wet market accessibility and urban housing prices and show that the negative influence of low-scoring markets is statistically larger than the positive influence of high-scoring wet markets. Further, we argue that high-income dwellers tend to pay more for perceived quality than for convenience.

Chapter 3 investigates the welfare effect of environmental quality at the intra-city level. With an instrumental variable approach, we assess the dynamic economic value of $PM_{2.5}$ on housing prices in Beijing between 2013 and 2019. Our results show that households are willing to pay to reduce air pollution. The mean willingness to pay peaked in 2015, and then decreased, possibly because of policy-based pollution mitigation strategies. Besides, the marginal willingness to pay for improving air quality varied across income groups: People with high incomes are more willing to pay a premium for clean air than those with low incomes.

Chapter 4 examines the welfare effect of urban planning policy at the inter-city level. Taking as a case study the Chinese city of Kaifeng — a suburban city in the Zhengzhou megaregion — we utilize spatial econometrics to investigate the effect of Kaifeng's integration with the core city of Zhengzhou on the dynamics and determinants of housing prices between 2001 and 2016. The results show that housing prices in Kaifeng increased significantly after the city's integration with Zhengzhou in 2005 and confirm that regional integration had a significantly positive effect on housing prices. This effect was achieved through a new time-saving cross-border light rail system, a new expressway, and new urban districts with high-quality amenities, especially in border areas between the cities.

Chapter 5 investigates the dynamic convergence of regional housing prices at the regional level. Taking housing price trends of 70 major cities between 2006 and 2017, we detect club convergence in housing prices across Chinese regions and examine the determinants influencing club formation. We find regional housing prices face heterogeneous dynamics and form four convergence clubs of Chinese regions with different convergence levels, thus providing some evidence of housing market segmentation. The clubs we identify contain cities from different Chinese city tiers and differ in their urban healthcare provision; other factors predicting club membership are population growth, income, and housing regulations.

Chapter 6 summarizes the main conclusions, highlights research implications, and discusses policy implications. It also discusses the limitations of this thesis and suggests directions for future research.

Nederlandse samenvatting

De link tussen steden en welvaart wordt hevig bediscussieerd in de economische geografie, regionale/stedelijke economie en andere gerelateerde disciplines. Vragen over de relatie tussen stedelijke groei en het welzijn van stadsbewoners zijn talrijk vanwege de complexe manier waarop stedelijke groei en de activiteiten van bewoners elkaar beïnvloeden, vooral in steden in opkomende landen met snelle verstedelijking. Met China als voorbeeld onderzoekt deze dissertatie hoe stedelijke groei het welzijn van bewoners in de stad beïnvloedt met behulp van de dynamiek van de huizenmarkt.

Dit onderzoeksthema wordt verder uitgewerkt vanuit vier invalshoeken. Ten eerste, hoe beïnvloeden stedelijke voorzieningen en nadelen – in dit geval verenigd in de *wet markets* ('natte markten') het welzijn van bewoners, zoals gemeten via huizenprijzen? In hoeverre zijn er verschillen in deze invloeden tussen bewoners met een hoog en laag inkomen? Ten tweede, wat is het effect van luchtkwaliteit op het welzijn van bewoners binnen de stad? Ten derde, hoe veranderen stedelijke huizenprijzen in de context van regionaal integratiebeleid? Hoe beïnvloedt integratiebeleid de stedelijke huizenprijzen in verschillende stadia van integratie? Ten vierde, is er sprake van clubconvergentie van regionale huizenprijzen in de steden van China? Zo ja, welke soort stedelijke factoren zijn mogelijke drijfveren?

De hoofdinhoud van elk hoofdstuk kan als volgt worden samengevat.

Hoofdstuk 1 presenteert de onderzoeksmotivatie, schetst de achtergrond van stedelijke groei in China en bespreekt onderzoeksvragen en onderzoeksmethoden.

Hoofdstuk 2 onderzoekt het welzijnseffect van stedelijke voorzieningen in hun sociale en milieu-dimensies op intra-stedelijk niveau. Door gebruik te maken van gegevens over woningtransacties in Beijing in 2019 en online review-scores van *wet markets*, onderzoeken we zowel de voor- als de nadelen van dergelijke markten en nemen we objectieve en subjectieve perspectieven in overweging. Onze resultaten geven een niet-lineaire relatie weer tussen de toegankelijkheid van natte markten en de huizenprijzen in de stad en tonen aan dat de negatieve invloed van laag scorende markten statistisch groter is dan de positieve invloed van hoog scorende natte markten. Verder stellen we dat bewoners met een hoog inkomen over het algemeen meer betalen voor waargenomen kwaliteit dan voor gemak.

Hoofdstuk 3 onderzoekt het welzijnseffect van milieukwaliteit op intra-stedelijk niveau. Met behulp van een instrumentele variabele benadering beoordelen we de dynamische economische waarde van $PM_{2.5}$ op huizenprijzen in Beijing tussen 2013 en 2019. Onze resultaten tonen aan dat huishoudens bereid zijn te betalen om luchtvervuiling te verminderen. De gemiddelde bereidheid om te betalen piekte in 2015 en daalde daarna, mogelijk vanwege beleidsstrategieën voor vermindering van luchtvervuiling. Bovendien varieerde de marginale bereidheid om te betalen voor het verbeteren van de luchtkwaliteit tussen inkomensgroepen: mensen met een hoog inkomen zijn meer bereid om een premie te betalen voor schone lucht dan degenen met een laag inkomen.

Hoofdstuk 4 onderzoekt het welzijnseffect van stedelijk planningsbeleid op interstedelijk niveau. Met de Chinese stad Kaifeng een voorstad van de Zhengzhou-megaregio als casestudy, maken we gebruik van ruimtelijke econometrie om het effect van de integratie van Kaifeng met de kernstad Zhengzhou op de dynamiek en determinanten van huizenprijzen tussen 2001 en 2016 te onderzoeken. De resultaten tonen aan dat huizenprijzen in Kaifeng aanzienlijk zijn gestegen na de integratie van de stad met Zhengzhou in 2005 en bevestigen dat regionale integratie een significant positief effect had op huizenprijzen. Dit effect werd bereikt door een nieuw tijdbesparend grensoverstijgend lightrailsysteem, een nieuwe snelweg en nieuwe stadsdistricten met hoogwaardige voorzieningen, vooral in grensgebieden tussen de steden.

Hoofdstuk 5 onderzoekt de dynamische convergentie van regionale huizenprijzen op regionaal niveau. Door de huizenprijsontwikkeling van 70 grote steden tussen 2006 en 2017 te analyseren, detecteren we convergentieclubvorming in huizenprijzen van verschillende Chinese regio's en onderzoeken we de determinanten die clubvorming beïnvloeden. We zien dat regionale huizenprijzen heterogene dynamieken hebben en vier convergentieclubs vormen met verschillende convergentieniveaus, wat bewijs levert van segmentatie op de huizenmarkt. De clubs die we identificeren bevatten steden uit verschillende Chinese stedenlagen en verschillen in hun gezondheidszorgvoorzieningen; andere factoren die clublidmaatschap voorspellen zijn bevolkingsgroei, inkomen en woningvoorschriften.

Hoofdstuk 6 vat de belangrijkste conclusies samen en bespreekt implicaties voor onderzoek en beleid. Het hoofdstuk behandelt ook de beperkingen van deze dissertatie en presenteert enkele suggesties voor toekomstig onderzoek.

Curriculum Vitae

Yuanyuan Cai was born on the 23rd of November 1989 in Zhengzhou, China. Between 2009 and 2013, she obtained a Bachelor's degree in International Economics and Trade from North China University of Water Resources and Electric Power (NCWU). From 2014 to 2017, she pursued her master's degree in Regional Economics, jointly trained by Henan University (HENU) and Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences (NIGLAS). She was awarded the "Best Master's Thesis Award" by Henan University in 2017 and the Department of Education of Henan Province in 2018 separately. Meanwhile, she received the honorary title of "Excellent Postgraduate" in Henan Province from the Department of Education of Henan Province in 2017. In September 2019, she began her PhD in Economic Geography, Department of Human Geography and Planning, at Utrecht University (UU).

List of Publications

First author

Cai, Y., & Gao, J. (2022). Unearthing the value of wet markets from urban housing prices: Evidence from Beijing, China. *Habitat International*, 122, 102532.

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