ABSTRACT

Title of Dissertation:	URBANIZATION AND ADVANTAGES OF LARGE CITIES: THREE ESSAYS ON URBAN DEVELOPMENT IN CHINA
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This dissertation, consisting of three essays on the urban development in China, provides empirical evidence for three related but different topics: urban growth pattern, agglomeration effects in production (production-side benefits of cities), and agglomeration effects in consumption (consumption-side benefits of cities).

The first essay examines the growth pattern of Chinese cities at prefectural level or above by applying a non-parametric analysis. The kernel regression reveals the coexistence of a divergent growth pattern for large cities and a convergent growth pattern for small cities. The analysis comparing two different kinds of population data shows that excluding migrant workers in the count of urban population would underestimate the size and growth of large cities, which implies that rural-urban migrants move to large cities disproportionately. The results suggest that policies trying to control the growth of large cities have been ineffective in the past two decades.

Using plant-level data in China, the second essay finds that the mechanisms of agglomeration economies vary with industry groups, and there is strong evidence supporting that regional industrial dominance would limit localization economies and diminish the productivity of firms. However, negative effects of regional industrial dominance seem to be mitigated by a large and diverse urban environment. The conclusion points to the productivity-enhancing effect of agglomeration, and a competitive industrial structure is crucial for the success of the on-going industrial transformation and upgrading in China.

Using survey data from China, the third essay reveals a positive relationship between city size and various categories of household consumption expenditures in China. By addressing several potential econometric issues, the analysis finds strong evidence of the agglomeration effect in consumption, which points to the important role that large cities play in enhancing household consumption.

Taken together, this dissertation concludes that large cities in China have been dominant during the rapid urbanization and tend to keep growing disproportionately. Large cities in China are more productive and provide higher consumption amenities than small cities. Therefore, a market-driven urbanization process would be more efficient and effective for enhancing both productivity and consumption in China.

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by

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Dedication

This dissertation is dedicated to my parents and my wife for all the love they have given me. Without their unwavering support, I would not have been able to complete this work.

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Chapter 1: General Introduction

1.1 Motivation and Research Questions

Urban economics is a branch of microeconomics that studies the location choice of households and firms. One of the prominent contributions of urban economists is providing explanations on why and how cities grow and why there are cities of different sizes and economic structures. China is still in the transition from a planned economy to a market-driven economy, which presents a unique context to study these issues, as the development of cities in China is influenced by not only market forces but also institutional and political factors.

Since the economic reform in the 1980s, it has only taken China three decades to have the largest urban population in the world. As predicted by the World Bank, urban population in China will increase by around 250 million in the next 15 years. Thus, it is important to understand the growth pattern and the forces that drive urban growth in China to envision where future growth may take place (large cities versus small cities), which is vital to China's economic and political future.

The idea of agglomeration economies plays a central role in urban economics in explaining the market forces in city growth and the differences in size and economic structures of cities. Agglomeration economies refer to the external benefits that firms/workers/consumers can obtain from locating near each other. These benefits are determinants of the attractiveness of a city and explain the existence and growth of large cities and clusters of economic activities. These benefits can be in both production side and consumption side. On the production side, agglomeration economies can lower production costs, enhance productivity and promote innovation through intermediate input sharing, labor market pooling and knowledge spillover. Firms and workers can be more productive in large cities. On the consumption side, a larger urban market can enhance consumption by providing a greater variety of consumption goods and services that are more tailored to consumers' tastes.

Cities in China are not only economic entities but also political cities. The strict administrative hierarchy of the city system allows large cities, which are always the ones at the upper level, have greater autonomy in decision making, more public finance resources, better access to regional transportation, etc. Hence, the political significance of large cities further reinforces their growth.

While both market forces and institutional setting in China favor large cities, national urbanization strategies have made great effort to address "urban diseases" in large cities such as traffic congestion, pollution and high housing costs by strictly controlling the growth of large cities, such as establishing a ceiling population for mega-cities. The question is: Have these growth control strategies been effective? If not, what forces drive the growth of large cities in China?

Motivated by both the contradiction between theoretic implication and national policies and goals and the tension between market forces that favor large cities and political influences that try to control the growth of large cities, this dissertation applies urban economic theories to address several key issues on the urban development in China. The first essay examines the growth pattern of Chinese cities and, more specifically, whether city growth follows a divergent pattern where bigger cities grow faster or a convergent pattern where smaller cities grow faster.

The second essay looks at the production-side benefits of large cities in China by examining both direct effects and interaction effects of industrial agglomeration and regional industrial dominance on firm-level productivity.

The third essay investigates the consumption-side benefits of large cities in China by examining the effect of city size on various categories of household consumption expenditures.

1.2 Research and Policy Significance

Understanding the current growth pattern is important for projecting future growth, which is crucial for determining the provision of infrastructure and urban services. Differing from previous studies on urban growth in China, the first essay applies a non-parametric analysis and reveals the coexistence of both a divergent growth pattern for large cities and a convergent growth pattern for small cities. Based on the comparison between two different kinds of population data, this study argues that previous analyses on urban growth in China may underestimate the size and growth of large cities as they exclude rural-urban migrant workers in the count of urban population. Rural-urban migration is disproportionately attracted to large cities, leading large cities to grow faster than small cities. The findings suggest that the national strategy that tries to strictly control the growth of large cities has had no effect in the past and the large cities may be dominant and continue to grow in the near future. Hence, large cities should prepare themselves to accommodate substantial population surges by providing more efficient infrastructure and urban services in order to promote sustainable growth rather than trying to limit the growth.

The second essay directly contributes to the empirical debate in the agglomeration literature on the relative importance of various sources and types of agglomeration economies in enhancing productivity. In addition, this study fills an empirical gap in the literature regarding how regional industrial dominance limits agglomeration economies and diminishes productivity. The conclusion shows that different industry groups benefit from different mechanisms of agglomeration economies and regional industrial dominance would diminish productivity by limiting agglomeration economies. This study is particularly relevant to the current industrial transformation and upgrading in China. The results have profound policy implications on how to create regional/local economic environments to make the best of agglomeration economies to promote productivity growth for different types of industries.

The third essay contributes to an emerging but important agglomeration literature that emphasizes the agglomeration effect in consumption. By using survey data from China, the analysis lends support to the theoretical expectation that large cities can enhance household consumption. This finding also points to the crucial role of large cities during the transition to a consumption-driven economy in China. An efficient market-driven urbanization process would be more effective in promoting household consumption.

1.3 Organization

The dissertation is organized as follows. Chapter 2 is an essay on urban growth pattern in China, titled “Size and Urban Growth of Chinese Cities during the Era of Transformation toward a Market Economy”. Chapter 3 and Chapter 4 focus on the production-side and consumption-side benefits of large cities in China, respectively. Chapter 3 presents the second essay, titled “Agglomeration economies and regional industrial dominance in China: An analysis of firm-level productivity”. Chapter 4 presents the third essay, titled “Consumption and City Size: Evidence from China.” Chapter 5 gives a general conclusion of this dissertation.

Chapter 2: Size and Urban Growth of Chinese Cities during the Era of Transformation toward a Market Economy

2.1 Abstract

This study examines the growth pattern of Chinese cities at prefectural level or above by first applying a non-parametric method. Kernel regression of the mean of growth rate conditional on city size reveals a U-shaped relationship between city growth and city size, which rejects Gibrat's law. More specifically, large cities take the form of divergent growth while small cities are convergent to each other. This U-shaped growth-size relationship holds for the registered (*hukou*) population in 1989–2012 as well as for the permanent population in 1999–2012. Furthermore, the results show that the growth of large cities becomes more divergent and the growth of small cities becomes less convergent when using the permanent population than using the registered population. The permanent population counts a portion of floating population, so it is then concluded that rural-city migrants tend to move to large cities disproportionally, making large cities grew faster. The registered population may underestimate the size and growth of large cities, since it does not include migrant workers. The conclusion is further substantiated by the OLS rank-size regression and panel unit root tests. The findings have profound policy implications. The national strategy of urbanization that has emphasized the growth controls of mega and super-big cities has had no significant impact in the past and may continue to be ineffective in shaping the urbanization trajectory in China in the next a couple of decades. Large

cities should prepare themselves in accommodating fast population growth rather than attempting to limit the growth.

2.2 Introduction

The beginning of the second decade of the 21st century marked the first time in Chinese history when more people live in cities and towns than in the countryside. In 2011, about 691 million urban dwellers accounted for 51.27% of China's total population. The urban population in China has increased by nearly 520 million since 1978 (NSB, 2013). The number of cities has increased from 193 in 1978 to 658 in 2012.[1] The rapid urbanization in China, in tandem with exceptional economic growth, will have far-reaching influence in shaping the world in the 21st century.

Scholars in urban economics, geography, planning, and policy are particularly interested in the fundamental and intriguing question of whether or not there are specific growth patterns of the urban system during rapid urbanization. If yes, what are they? More specifically, does china's city system exhibit a convergent or divergent growth pattern, or follow a random process in which cities move together in the long run or grow purely independently. It should be noted that answers to these questions may have far-reaching policy implications in China. This is mainly because: 1) China is among only a few countries that have adopted a national strategy on urbanization (Ding & Zhao, 2011); and 2) China has strong non-market forces that affect local economic growth (Zhu & Kotz, 2010).

[1] Total urban population in 1978 was 172 million, with an urbanization rate of 17.9 percent.

This paper attempts to investigate the question using China as a case study. China offers a unique context to examine the growth patterns of the city system for the following reasons. First, China first introduced the national urbanization strategy of "strictly controlling the growth of large cities, moderately promoting the growth of medium-sized city, and encouraging the growth of small cities and towns" in the middle of the 1980s. This policy specifically targeted a convergent trajectory of the city system by inversely correlating city growth rate to city size. The policy was codified in the National Urban Planning Law of 1989. A notable change in the new strategy is that it strictly controls the growth of super-big cities (population of 5–10 million) and megacities (population of more than 10 million) but encourages the rapid growth of small- and medium-sized cities.[2]

Second, Chinese cities have administrative hierarchies in which cities are administratively ranked as province-level, vice-province-level, prefecture-level, and county-level cities. City's administrative ranks in China are linked to local governments' capacity regarding public spending, taxation, and capital projects, all of which would play important roles in local economic growth (Li, 2011). Administrative ranks of cities are a major factor in site selection decision for policy reform initiatives, pilot development projects, and the designation of various economic and social development zones (Wei, 2014). The importance of administrative ranks of cities is

[2] From 1980 to 2013, the size-based city classification was: a super-big city has a population of more than 1 million; a big city has a 0.5–1 million population; a medium-sized city has a 0.2–0.5 million population; and a small city or town has a population of less than 0.2 million. In 2014, the State Council modified and expanded this as: a megacity has a population of more than 10 million; a super-big city has a 5–10 million population; a big city has a 1–5 million population; and a medium-sized city has a 0.5–1 million population. Additional changes to these cut-off thresholds for city size include the formal recognition of the floating population and semi-permanent residents without city *hukou* in the city population count and abolishment of occupation-based city population counts (such as the distinction between the non-agricultural versus agricultural population).

further reflected in China's state capitalism and state-driven growth model as they implicitly or explicitly symbolize political power and connection.

Finally, China has a unique city-region governance structure, namely the "City-Managing-County" administrative system, which was first introduced in the 1950s and rapidly spread in the 1980s. Typically, a city-region region is composed of a prefecture-level city (or equivalent at the administrative level) and several county-level cities and/or counties. The city, which is also called the central city, has institutionalized administrative roles for managing growth and development of county-level cities and counties through the so-called "City-Managing-County" system (here county may also stand for county-level city). Under the "City-Managing-County" system, city governments often take advantage of this institutional power to promote the growth of central cities at the expense of rural counties and county-level cities (Yang & Wu, 2015).

The combination of rapid urbanization during the transformative period, the national urbanization strategy, and the unique city administrative structure makes China an interesting case to examine urbanization patterns and better understand the dynamics of city evolution under market forces. This examination is important for both intellectual curiosity as well as the practical consideration for policy and planning implications. General research questions for the examination include, but are not limited to: How has China's city system evolved during the rapid urbanization? Does it converge or diverge? Has the growth of cities followed the national urbanization strategy? Does the evolution of the city system exhibit variations across regions that are significantly different from each other in terms development status, physical and natural resource endowment, and people-land tension? How and to what extent does China's unique city political system influence its urbanization patterns? Do miscount of floating population (migrant workers) or other data issues in China's statistical yearbooks produce empirical results that lead to misunderstanding urbanization patterns in China?

Among these questions, this study focuses on the question of convergence versus divergence in the growth of Chinese cities in the period of 1989–2012 when the economy grew remarkably. Following the literature, I approach the question by examining the rank-size rule [3]and Gibrat's law[4] on a panel data set, as well as by looking at non-linearity of the size-growth relationship. Unlike the literature, I apply a non-parametric method to estimate the mean and variance of growth rates conditional on city size and to reveal the non-linearity between growth rate and city size, which I believe is the first use for Chinese cities. The non-linear relationship is further explored by examining the local Zipf exponent as a robustness check. I also run OLS estimates for the rank-size rule to investigate specifically the size-growth relationship among big cities. Finally, I use two different types of population data to address the estimation bias resulted from measurement errors; I further run the analyses by sub-periods, balanced and un-balanced panels, and subsamples to determine if there are both time and cross-section variations in growth patterns of Chinese cities.

[3] Rank-size rule suggests that city size distribution for the upper tail follows Pareto distribution and the Pareto exponent or Zipf exponent equals 1(Gabaix, 1999). This also implies a log-linear relationship between city size and city rank.
[4] Gibrat's law implies a parallel or proportionate growth model where cities grow randomly with the same expected growth rate and same variance, both of which are independent of city size (Gabaix, 1999; Eeckhout, 2004).

The paper is organized as the follows. Section 2.3 briefly discusses the political and administrative structure of Chinese cities, followed by a literature review in Section 2.4. Section 2.5 discusses data and methods in general. Section 2.6 presents results, and section 2.7 shows some robustness checks. Section 2.8 gives conclusions and final remarks.

2.3 The Politics of Chinese Cities

Chinese cities are differentiated by their legislative and administrative status. Province-level cities have the same legislative and administrative authorities as provincial governments, which are institutionalized to establish and pass local laws, subject to the requirement of non-contradiction to the Constitution, laws, and regulations passed by the central government. This legislative power is only institutionalized to province-level cities. There are four province-level cities: Beijing, Shanghai, Tianjin, and Chongqing. The importance of province-level cities is also reflected in the political status of a city's party secretary as a member of the Politburo, which is the most powerful decision body of Communist Party of China (CPC).

Vice-province-level cities are authorized by the central government to have much greater freedom and power in creating their own economic development plans than all other cities except province-level cities. These cities were first singled out as so-called *jihua danlie* cities in the 1980s. *Jihua danlie* city means that its economic growth targets are determined or allotted by the central government rather than provincial governments. That is, vice-province-level cities plan their economic growth according to national plans rather than provincial ones. As the economic importance of those *jihua danlie* cities increases, they were promoted into vice-province-level cities in 1994. Another important aspect of vice-province-level cities is that they split their taxes with the central government rather than the provincial government.[5]

Prefecture-level cities are the second tier in the subnational governments as *diji* administrative units in China. Prefecture-level cities are distinguished in two different aspects. First, they are economically vibrant and many serve as regional growth engines. The criteria used to establish a prefecture-level city partly reflect this type of city's importance in the national economy. The criteria are: the sum of annual local gross industrial and agricultural output value must be over 3 billion RMB, of which the gross industrial output value should account for over 80%; the local annual GDP must be over 2.5 billion RMB, of which the service industry should account for over 35%; the local annual financial budgetary revenue must exceed 200 million RMB; and the city must be considered a "central city" (China's Association of Mayors, 2012). A central city is expected to play a leading role in promoting regional development, balancing growth within the region where it is situated, and reducing urban-rural inequality. The leading roles of prefecture-level cities are further reinforced by the widely adopted regional governance structure of the "City-Managing-County" system (*shi guan xian*). Both the notion of "central city" and the "City-Managing-County" system were introduced to promote regional balanced growth and reduce urban-rural inequality.

[5] There are 15 deputy-province-level cities: Guangzhou, Shenyang, Nanjing, Wuhan, Chengdu, Xi'an, Dalian, Changchun, Harbin, Jinan, Qingdao, Hangzhou, Ningbo, Xiamen, and Shenzhen. Chongqing was promoted from a deputy-province-level city to a province-level city in 1997.

There are two ways to become a prefecture-level city. One is through the *diqu*-city conversion (so-called *di-gai-shi*, or *che-di-she-shi*). [6] The other is through the upgrade from a county-level city. Both need approvals from the State Council. The *diqu*-city conversion also involves the upgrade of a county-level city, which usually is the capital city of the *diqu*'s administrative areas. [7] The *diqu*-city conversion is the main reason for the rising number of prefecture-level cities. For instance, 121 prefecture-level cities were created through the *diqu*-city conversion in 1980–2010, accounting for two-thirds of new prefectural cities.

The last tier in the city system is county-level cities. There were 368 county-level cities in 2012. County-level cities report to prefecture-level cities. In a prefecture, county-level cities and counties are subordinated into a single city (usually a prefecture-level city) that administrates the entire prefecture.

Figure 1 illustrates the functional relationship between a prefecture-level city and county-level cities under the "City-Managing-County" administrative structure. Under this structure, a prefecture-level city, which is also a central city, is expected to lead the regional economic growth, promote rural-urban harmonious growth, and reduce rural-urban income gaps. For instance, Jilin City, a prefecture-level city, is the second largest city in Jilin province. Beside its own four municipal districts (Changyi, chuanying, Longtan, and Fengman), the city government is also designated to manage

[6] *Diqu* administrative commissions, ranked as same as prefecture-level cities in the administrative system, are not independent sub-governments. Rather, they are representative agencies of provincial governments. *Diqu* administrative units tend to locate in the remote and less developed areas.

[7] Most *diqu*-city conversions create one city, but there are a few cases in which multiple prefecture-level cities were created. For instance, Tonghua *diqu* in Jilin province was divided into three prefecture-level cities: Tonghua, Hunjiang, and Meihekou.

the economic affairs and growth of 5 adjacent counties/county-level cities: Huadian, Jiaohe, Panshi, Shulan, and Yongji.

<Figure 1 here>

First, cities at the top of the ranks are more favored regarding economic development than cities at the bottom. Cities at the top of the administrative ranks are always large cities, so the administrative ranking of Chines cities characterizes urbanization in China as having a bias toward big cities. The bias of urbanization toward big cities under the unique administrative ranking of Chinese cities is supported by anecdotal evidence. For instance, the primacy of provinces increased from 2006 to 2012. The ratio of the population of the largest city to the population of the second largest city during this period increased in 20 out of 24 major provinces.[8] The four provinces with a declining or staggering primacy are Gansu, Shanxi, Jiangxi, and Guizhou, resulting from little growth of their capital cities.

Second, under the "City-Managing-County" system, county-level cities are at great disadvantage for economic growth as they are at the bottom of the administrative ladder. Prefecture-level cities often intercept a substantial portion of intergovernmental transfers to counties and county-level cities (Wei, 2014). In order to finance urban infrastructure and capital projects to enhance local economic growth, prefecture-level cities have strong incentives to use their administrative powers and authorities to take away capital resources and off-budget revenues from counties and county-level cities. In addition, county-level cities benefit little from their central cities (prefecture-level

[8] Seven provinces were excluded, including four provincial-level cities and three provinces (i.e., Tibet, Qinghai, and Hainan) that are not significant in the urban system in terms of number of cities and total urban population. For Fujian, Guangdong, and Shandong, primacy was calculated using the third largest city rather than the second largest city because the second largest cities are vice-provincial-level cities.

cities), because many prefecture-level cities, especially those in the central and western regions, do not have local economies strong enough to allow the cities to function as regional economic growth engines (Yang & Wu, 2015). As a result, counties and county-level cities have been suffering from stagnation, and the rural-urban income gap has been rising (Wei, 2014).

The influences of administrative ranking system of Chinese cities on urbanization are materialized through the following mechanisms:

- Cities at the top have more administrative powers and authorities in policy-making and allocation of administrative resources to mobilize economic factors to promote local economic growth. Province-level cities were 4.22 times and 3.24 times as large as county-level cities and prefecture-level cities, in terms of per capita investment in urban infrastructure in 2006, respectively; these numbers were 1.98 and 1.52 for capital cities of provinces (Wei, 2014). City administrative ranks are positively correlated with the provision of urban infrastructure such as wastewater treatment facilities, household usage of gas, and per capita hectare of open space/parks (Wei, 2014).
- A direct consequence of the 1993/94 fiscal reform is the rising fiscal deficit of subnational governments, particularly at the lower ladder of the administrative hierarchy (Ding et al., 2014; Wei, 2014). The reform centralized tax revenues upward along the ladder of the administrative hierarchy and decentralized public spending downward (so called "*cai quan shang shou*, *shi quan xia yi*"). Cities at the lower level of the administrative

ranks benefit little from the state-led growth model that emphasizes investment-driven growth.

- Cities at the top tend to be political centers (e.g. provincial capitals) where social and human capitals are disproportionally concentrated. Universities, research institutes, large hospitals, and financial institutes are clustered in political centers, such as provincial capitals, which are also regional hubs of the national transportation network. Advantages in urban amenities and the great accessibility to transportation network make cities at the top of administrative ranking more favorable to attract foreign direct investment (Wei, 2014).
- Cities at the top are also favored in the institutional setting and reforms toward a market economy. The central government tends to choose cities at the top of the administrative ranking to experiment major reforms, such as the special economic development zones or free trade zones.

2.4 Growth of Cities: Theory and Empirics

2.4.1 Theory

Regarding growth pattern of cities, there are three types of theories: parallel growth, convergent growth and divergent growth. Theories predicting or implying parallel growth of cities include the endogenous growth theory (Black & Henderson, 1999; Eaton & Eckstein, 1997), random growth theory (Cordoba, 2008; Gabiax, 1999), and locational fundamentals theory (Fujita & Mori, 1996; Krugman, 1996). Theories predicting convergent growth of cities include the trade and export theory (North, 1955) and neoclassical exogenous growth theory (Barro & Sala-i-Martin, 1999). Theories predicting divergent growth of cities include the cumulative causation theory (Dixon & Thirlwall, 1975) and growth pole theory, which was abandoned in 1980s (Dawkins, 2003).

A sequential development model has been proposed (Cuberes, 2011). The model suggests a bell-shaped growth pattern in which large cities grow first and small cities grow subsequently. The micro-foundation for the bell-shaped growth pattern is that the force of scale of economies enables large cities to grow, or grow faster, than small cities at an early stage of development. The benefits of scale become weaker than negative externalities (congestion and pollution) as development continues so that small cities grow, or grow faster, at a later stage of development. This implies that urbanization is biased toward large cities in an early development stage.

Among these theories, the random growth theory has drawn significant attention. It not only predicts parallel growth of cities but also, more importantly, produces a stable city size distribution that follows Zipf's law. Specifically, according to the model, cities grow randomly with the same expected growth rate and same variance, both of which are independent of city size (Gabaix, 1999; Eeckhout, 2004).

2.4.2 Empirics

Empirical studies are rich and extensive with regard to the growth of cities. By analyzing the distribution of the populations of the top-40 urban areas of France and Japan, Eaton and Eckstein (1997) concluded that urbanization takes the form of parallel growth of cities, rather than convergence to the optimal size distribution or divergence, which favors large cities. Sharma (2003) concluded that Indian cities grow in a parallel fashion in the long run. Ioannides and Overman (2003) used the entire sample of metropolitan areas in the US during 1900 and 1990 and concluded that Gibrat's law cannot be formally rejected, even though the mean and variance of growth rates vary with city size, suggesting that the trajectories of growth are parallel for cities. Eeckhout (2004) echoed their conclusion by confirming Gibrat's law in the period of 1990–2000. González-Val (2010) found that Gibrat's law weakly holds for U.S. incorporated places in the long-run. González-Val et al. (2014) tested the validity of Gibrat's law using data covering the complete distribution of cities in the United States, Spain, and Italy from 1900 to 2000. The results of nonparametric estimates indicated that mean growth rates seem to be independent of city size in these three countries in the long term.

There is substantial coverage in the literature of the size distribution of cities and its evolution over time. Without changes in rank order, a stable size distribution of cities over time implies a parallel growth pattern of cities. A majority of studies provide evidences suggesting a stable size distribution over time (Black & Henderson, 2003; Eaton & Eckstein, 1997; Ioannides & Overman, 2003).

City growth may take the form of either divergence or convergence in the short run or depend on the development stage/period. González-Val (2010) found that large cities grow faster in periods of high economic growth, and small cities grow faster in periods of crisis. González-Val et al. (2014) concluded that city growth exhibited a divergent pattern in Spain and Italy during the first half of the century and a convergent growth pattern in the second half, especially among medium-sized and large cities. Studies by GueArin-Pace (1995), Black and Henderson (2003), Wheaton and shishido

(1981), Junius (1999), Davis and Henderson (2003), and Cuberes (2011) also found the growth pattern of divergence first and convergence later over time is also found in.

Moomaw and Shatter (1996) presented evidence supporting the argument that urbanization is biased toward large cities. Ades and Glaeser (1995) concluded that large cities are favored to grow in the presence of high transportation costs, a politically dictated system, and a lack of openness to international trade.

There are mixed results in the examination of the growth of Chinese cities. Song and Zhang (2002) and Xu and Zhu (2009) found an increase in the Zipf exponent during the 1990s, implying a convergent growth pattern. Anderson and Ge (2005) suggested that the size distribution of Chinese cities was stable before the economic reform and that a convergent growth pattern was present during the period of 1980–1999. Schaffar and Dimou (2012) found mixed results that urban growth exhibited convergent behavior in 1984–1994 and divergent behavior in 1994–2004. Chen et al. (2013) found that the growth of Chinese cities is random based on estimates of the rank-size rule and unit root tests, revealing parallel growth in the period of 1984–2006. Henderson (2009) concluded that large cities are favored to grow because they are ranked high in the hierarchy of the city system and enjoy greater autonomy in decision making, more public finance resources, and better access to regional transportation.

The inconsistent conclusions about growth patterns of Chinese cities are largely due to estimation problems and data issues. Estimation problems arise for the following reasons. First, changes in sample size during the study period may affect the estimated coefficients, particularly for the Zipf exponent (Eeckhout, 2004). The number of both total cities and prefectural cities steadily increased from 193 and 98 in 1978 to 657 and

289 in 2012, respectively. Therefore, it would not be surprising that the estimated results using all cities would be different from those using only prefecture-level cities. Second, rank-size OLS regression would produce a biased estimation when the underlying true distribution of city size is lognormal (Eeckhout, 2004). Third, a whole city sample may not follow the same distribution. For instance, only the upper tail of the city size distribution follows Pareto distribution, a critical condition for the holding of Zipf's law (Gabaix, 1999; Ioannides & Skouras, 2013). Fourth, rank-size OLS regression cannot reflect the evolution of city size distribution, which varies with city size (Garmestani et al., 2008).

Data used to represent city size are problematic, which may cause discrepancies in estimation results. Previous studies on China have used either the non-agricultural population (Song & Zhang, 2002; Xu & Zhu, 2009; Chen et al., 2013; Henderson, 2009) or the total population in city administrative areas (Anderson & Ge, 2005; Schaffar & Dimou, 2012). Neither the non-agricultural population nor total population accurately represent the size of cities. The non-agricultural (registered) population underrepresents true city size because it excludes the floating population and agricultural population living and working in the city proper. The total (registered) population over-represents city size because it includes the rural population, which is not part of the urban economy. This overestimation is significant for (small) cities with relatively small city proper areas. Nevertheless, both types of data may substantially under-represent true city size for large cities as they are primary destinations of a massive floating population that is believed to be in the range of 100–250 million. Underreporting (or missing) of massive rural-urban migrants (called the floating population) physically working and living in cities will definitely produce biased results and misinform policy implications.

2.5 Data

This study uses two different data sources: (1) China City Statistical Yearbook 1990-2013, covering the period of 1989-2012; and (2) China Urban Construction Statistical Yearbook 2000-2013, covering the period of 1999-2012.[9] Each data set has its own merits, as shown in Table 1.

<Table 1 here>

China City Statistical Yearbooks provide population data based on household registration system (*hukou*), by sectors (agricultural vs. non-agricultural) and by geography (city proper vs. entire administrative area of a city).[10] I use the total registered (*hukou*) population in city proper to proxy city size.

Compared with the total registered population of the entire administrative area of a city and registered non-agricultural population used in previous studies, total registered population (including both the registered agricultural and non-agricultural population) in the city proper more accurately represents city size in China's transformation toward a market economy. This is because members of the registered agricultural population in the city proper (including peri-urban areas) are more likely employed in non-agricultural sectors, as is the case in the Pearl Delta and Yangtze Delta regions, and should be counted as part of the urban population. Excluding these populations, the registered non-agricultural population in the city proper will result in

[9] China Urban Construction Statistical Yearbook is only available after 1999.
[10] Since 2009, population by sectors (agricultural vs. non-agricultural) is no longer reported.

the underestimation of city size. Counting people living outside built-up city areas (such as the registered non-agricultural population in towns outside the city proper and the agricultural population in rural areas) will result in an overestimation of city size, so that both the non-agricultural and total population of the entire administrative area may over-represent city size. Thus, I believe that using the total registered population in the city proper is better than using the non-agricultural population and total population of an entire administrative area when examining the growth patterns of Chinese cities.

The main drawback of using the registered population is the omission of the floating population (migrant workers). The registered city population excludes the floating population holding rural *hukou* but working in cities and towns. The combination of industrialization, the development of a market economy, and labor reforms has produced a massive floating population. It is estimated that the floating population numbered 121 million in 2000 and increased to 236 million in 2012 (NSB, 2013). It is apparent that excluding the massive floating population will substantially under-represent city size and city growth, especially for large cities that attract a disproportionately large portion of migrant workers.

To address this issue, this study also uses data from China Urban Construction Statistical Yearbooks, which provide permanent population data in built-up areas. The permanent population data from China Urban Construction Statistical Yearbooks addresses this issue, at least partially, by taking into account the floating population continuously living in cities or towns over six months. This greatly improves the accuracy of the population data in representing city size. Another major improvement by the data is associated with the fact that built-up areas are used, instead of the city proper, whose geographical territories may be not determined by urban spatial expansion but by administrative consideration. Merging and annexation of administrative units would cause dramatic changes of city-proper areas. [11] A major problem with the permanent population data, however, is that the definition of built-up areas changed in 2005–2006, which caused permanent city population increases or decreases for some cities (Table 1). From 1999 to 2005, population density, statutory street committees (*jiedao*), and contiguity of urban areas determined built-up city areas. Since 2006, these have been determined mainly by geographical contiguity of built-up urban areas.

Table 2 reports descriptive statistics of the data and compares two types of population data. Preliminary analysis of the data reveals interesting findings. First, there are significant discrepancies between the registered population (*hukou*) and permanent population. The mean of the permanent population is smaller than that of the registered population, which is also true for the median, implying that the registered population may overestimate city size in general. Second, there are substantial discrepancies between the two population data sets, particularly for large cities. If the permanent population is assumed to more accurately represent city size, the registered population underestimates the size of large cities and overestimates the size of small cities.

<Table 2 here>

[11] In the 1980s and 1990s, 50 *diqu*s (prefectural-level administrative units) were abolished and merged into 62 cities at the prefectural level or above.

Third and finally, the net growth of large cities is greater than that of small cities, indicated by rising skewness of both the registered and permanent population toward the right over time. The registered population underrepresents the growth of large cities compared to the permanent population. This is indicated by the fact that the increase in the skewness of the permanent population is larger than that of registered population. The conclusion is also supported by changes in the extreme values (min. and max.) of both the registered and permanent population.

It should be cautious to use both population data sets, which show some irregular changes over time caused by two different factors/reasons. The first reason is associated with changes in definitions (such as built-up areas), city administrative boundaries (expansion of the city proper) and inclusiveness/exclusiveness of the floating population. This explains the unusual growth of some cities. For instance, the population of the largest city, Shanghai, grew 17% in 2005–2006 and about 15% in 2010–2011 for the registered population, whereas the permanent population grew 23.5% in 2004–2005. I believe that those striking annual growth rates of Shanghai in fact capture accumulated growth that was missed in previous years, rather than actual annual growth. Chongqing incorporated 4 county-level cities into its municipal districts in 2006. As a result, the registered population in the city proper increased from 10.3 million in 2005 to 15.1 million in 2006.

The second reason is associated with data entry errors. For example, Baoshan had a permanent population of 17,800 in 2002, dramatically smaller compared to the number in 2001 and 2003. The registered population in the city proper of Dongguan increased from 1.3 million in 1990 to 1.6 million in 2004, and then suddenly jumped to 6.6 million in 2005 and dropped back to 1.7 million in 2006.

As a result, some cities show unusually high/low growth rates, creating outliers. I use the top 0.5% highest and the bottom 0.5% lowest normalized growth rates as cutoff values to identify outliers that are dropped from the sample used in the non-parametric analysis. The outliers include observations that are considered to be data entry errors (e.g., Dongguan in 2004–2006) or associated with changes in city-proper territories (e.g., Chongqing in 2005–2006). The sample ends up including 5,548 observations for the registered population for the period of 1989–2012 and 3,543 observations for the permanent population for the period of 1999–2012.

2.6 City Size and City Growth

2.6.1 Non-Parametric Analysis of City Growth

This study applies kernel regression to analyze city growth with respect to city size. The merits of the approach are three fold (Ioannides & Overman, 2003; Eeckhout, 2004; González-Val et al., 2014). First, the function form does not need to be pre-specified. This is important when the relationship between city growth and size may be unknown and non-linear. Second, estimates are less sensitive to changes in sample size over time compared to those from unit-root tests, rank-size type of regression, and regression of growth rate on city size. Third, this non-parametric method can identify local patterns that vary from the general trend of city growth.

Following González-Val et al. (2014) and Ioannides and Overman (2003), the mean of growth rate ($m(s_i)$) conditional on city size (s_i) is determined as:

$$g_i = m(s_i) + \varepsilon_i \qquad (1)$$

where g_i is the normalized growth rate and s_i is the natural logarithm of city i's relative size, which is the ratio of a city's size over the average size of all cities. The growth rate for city i during year t-1 to year t is defined as (s_{it}- s_{it-1}), and normalized growth rate is the growth rate for each city subtracting the mean and dividing by the standard deviation.

To estimate (1), I adopt the Nadaraya-Watson method, which is expressed as:

$$\widehat{m}(s) = \frac{n^{-1}\sum_{i=1}^{n} K_h(s - s_i)g_i}{n^{-1}\sum_{i=1}^{n} K_h(s - s_i)} \qquad (2)$$

Where, $\widehat{f_h}(s) = n^{-1}\sum_{i=1}^{n} K_h(s - s_i)$ is a kernel density estimator and $K_h(u) = h^{-1}K(u/h)$ is the kernel function on bandwidth h. Kernel regression is a weighted average estimator that uses kernel function as weight. Kernel is a continuous, bounded, and symmetric real function K that integrates to one (Härdle, 1990).[12] Following Gonzalez-Val et al. (2014), this study uses the Epanechnikov kernel function and bandwidth h of 0.5 for all estimations in order to make comparisons.

The variance in growth rate conditional on city size, $\hat{\sigma}^2(s)$, is estimated by the Nadaraya-Watson method, which is given as:

$$\hat{\sigma}^2(s) = \frac{n^{-1}\sum_{i=1}^{n} K_h(s - s_i)(g_i - \widehat{m}(s))^2}{n^{-1}\sum_{i=1}^{n} K_h(s - s_i)} \qquad (3)$$

If the growth rate is independent of city size, the conditional mean growth rate should be a straight line on zero, and conditional variance of growth rate should be a straight line on one, as the growth rate is normalized. An ascending line implies a

[12] The kernel regression estimator is consistent under general assumptions:

$\widehat{m}(s_i) \overset{P}{\rightarrow} m(s_i)$ if $h \rightarrow 0$ and $nh \rightarrow \infty$ as $n \rightarrow \infty$

divergent growth pattern in which larger cities grow faster, while a descending line implies a convergent growth pattern.

I apply Equation (2) by using both the registered population and the permanent population. I estimate Eq. (2) for the entire period as well as by breakdowns. Figure 2 shows the non-parametric estimates of means of growth rates conditional on city size. Three interesting findings are obtained from Figure 2. The first finding is that Gibrat's law does not hold well since: 1) the zero value line does not completely fall inside the 5% confidence band of means of growth rates (Figure 2), expect figure 2 (e); and 2) the one value line does not completely fall inside the 5% confidence band of variance of growth rates (Figure 3). Those results lead to the conclusion that the growth of Chinese cities do not take the form of parallel or random growth. The results are also confirmed by various panel unit root tests (see robustness check for detail).

The second finding is to reject a linear relationship between city growth and city size, as indicated by U-Shaped curves (Figure 2). This leads to the third finding of the coexistence of both divergent growth and convergent growth of Chinese cities. Small cities converge while large cities diverge. These three findings are robust regardless of data and period.

<Figure 2 here>

<Figure 3 here>

Figure 2 also reveals that when the permanent population is used, more divergent growth is found for large cities, compared to using the registered population. More specifically, a comparison between (c) and (f), between (d) and (g), and between (e) and (h) shows that the mean growth rate for large cities conditional on size is relatively stable when measured by the registered population, whereas the mean growth rate for large cities increases dramatically with relative city size when measured by the permanent population. I interpret the differences in Figure 2 as the fact that the registered population underestimate the size and growth of large cities since it excludes the massive floating population and migrant workers. This conclusion is also consistent with the general descriptive statistics (Table 2).

2.6.2 Non-Parametric Analysis of Local Zipf Exponent

An alternative way to examine the relationship between city growth and size is through an examination of changes in the local Zipf exponent (Gabaix, 1999; Ioannides & Overman, 2003; González-Val, 2012). By estimating the local Zipf exponent, cities in different size groups are allowed to have different distributions and different growth patterns. That is to say that the evolution of city size distribution may also vary with city size. The main merit of the approach is that it enables me to examine the possibility that cities of different sizes have different growth patterns. In other words, it is able to reveal local patterns that may be different from the general rank-size relationship (Garmestani et al., 2008). Thus, I do not need to conduct analyses based on the assumption that all cities follow the same distribution and growth pattern in conventional rank-size regression.

Under Zipf's law, city size distribution should follow Pareto distribution, which is given by Eq. (4):

$$G(s) = As^{-a} \tag{4}$$

where s denotes the relative population in a city and $G(s)$ is the distribution function of city size; A and a are positive parameters; and a is Pareto or Zipf exponent and equals to 1 when Zipf's law holds.

Following Gabaix (1999), in case that cities grow randomly with the expected rates and the standard deviations that are dependent on their size, the size of a city is determined as:

$$\frac{dS_t}{S_t} = \mu(s)dt + \sigma(s)dB_t \qquad (5)$$

where, $\mu(s)$ and $\sigma(s)$ denote the mean and standard deviation of the growth rate conditional on city size s, and B_t stands for a geometric Brownian motion. In this case, the limit distribution of city size will converge to Zipf's law with a local Zipf exponent $a(s)$, which is a function of relative city size, conditional mean, and variance of growth rate, expressed as:

$$a(s) = 1 - 2\frac{\mu(s)}{\sigma^2(s)} + \frac{s}{\sigma^2(s)}\frac{\partial\sigma^2(s)}{\partial s} \qquad (6)$$

Eq. (6) is estimated by the estimated conditional means and conditional variance from the non-parametric analysis from Eq. (2) and (3).

I also estimate the local Zipf exponents by sub-periods and attempt to identify growth patterns between sub-periods by examining the changes in the local Zipf exponent over time. Assuming that Zipf's law may or may not hold in the short run (González-Val, 2012), increases or decreases in the local Zipf exponent between sub-periods are interpreted as convergent or divergent growth pattern, respectively.

I first estimate the means (Figure 2 b, c, f) and the variances ((Figure 3 b, c, f)) conditional on city size using the registered population and permanent population for two sub-periods (1989–1999 and 1999–2012) by the non-parametric method and then calculate the local Zipf exponent following Eq. (6).

Figure 4 illustrates estimated values of the local Zipf exponent conditional on city size. The figure reveals the following findings: 1) Zipf's law is generally rejected; 2) all values of the local Zipf exponent for different city sizes tend to converge to 1 over time; 3) there are systematic changes in the local Zipf exponent over time, which exhibits increases in the values for small cities and decreases in the values for large cities over periods. Interpreting these patterns leads to conclude that there is a mix of convergent growth for small cities and divergent growth for large cities between the two periods. The conclusion is consistent with the kernel regression analysis.

<Figure 4 here>

I also calculate the local Zipf exponent using the permanent population for the period of 1999–2012. It should be noted that the estimated values of the local exponent using the permanent population in 1999–2012 are smaller than estimated values using the registered population. I interpret this as the registered population resulting in the underestimation of size differences among cities.

The floating population first began to emerge in the 1980s and rapidly arose in the mid-1990s. It was not until the 21st century that these migrant workers began to permanently settle in cities and towns. Accordingly, if urbanization in 1989–1999 is considered to be with restricted spatial mobility and the urbanization in 1999–2012 to be without restriction, the registered population underestimates the size differences among cities and biases the growth patterns of small and large cities in 1999–2012. Using the permanent population as the reference, the registered population underestimates the divergent growth of big cities and overestimates the convergent growth of small cities. This is indicated by the fact that when the permanent population is used, the decline of the estimated values of the local Zipf exponent for big cities over periods is larger and the increase in the estimated values for small cities over periods is smaller, compared to using the registered population. The floating population explains the differences between the two data sets in 1999–2012. I interpret this as evidence that rural-urban migrants (floating population) have favored large cities during rapid urbanization in China, particularly in the period of 1999–2012, causing divergent growth of large cities.

2.6.3 Rank-Size OLS Regression

This study also conducts rank-size OLS regression to examine city size distribution and evolution of the city system over time. I estimate both the conventional rank-size relationship and an extended one.

The conventional rank-size relationship is expressed as:

$$\ln R_{it} = \ln A_t - \alpha_t \ln S_{it} + \varepsilon_{it} \qquad (7)$$

where, R_{it} is the rank of the city i in year t in terms of size; S_{it} is the population in city i in year t; and ε_{it} is an error term. An estimated value of α_t close to one suggests that Zipf's law holds.

Zipf exponent α_t measures the degree of urban concentration. A smaller exponent indicates a higher level of urban concentration. Empirically, the change of the estimated coefficient α_t over time would imply the growth patterns of cities. A constant value of the coefficient over time suggests parallel growth; an increase in the coefficient over time reveals a convergent growth pattern; and a decrease shows a divergent growth pattern.

In order to capture the possibility that the growth pattern of large cities differs from other cities, I introduce a dummy variable for large cities into Eq. (7), which is now expressed in an extended rank-size model as:

$$\ln R_{it} = \ln A_t - \alpha_{1t} \ln S_{it} - \alpha_{2t} D_l \ln S_{it} + \varepsilon_{it} \qquad (8)$$

where, D_l is a dummy variable, which equals one for large cities. Large cities are cities with an urban population of over one million or the top-50 largest cities. I expect the estimated α_{2t} to be significantly different from zero.

Tables 3 and 4 report the estimated results of Eq. (7) for the full sample, for sub-sample, and for the two different data sets. Two sub-samples are selected; one includes all cities with a population of over half a million, and the other includes all cities with a population of over one million. The results are summarized as follows. First, in all cases except the full sample of the permanent population, the estimated coefficients (exponents) are substantially larger than one, ranging from 1.20 to 1.32 for the registered population and from 1.02 to 1.15 for the permanent population. In addition, the estimated results show that large cities have a larger Zipf exponent. For instance, the mean of the estimated exponent using the registered population in 1990-2012 is 1.235 for the full sample, 1.538 for cities with a population of over 0.5 million, and 1.739 for cities with a population of over one million. This is also true when using the permanent population. The mean of the estimated exponent in 2000–2012 is 1.056 for the full sample, 1.32 for cities with a population over 0.5 million, and 1.434 for cities with a population of over one million population.

<Table 3 here>

<Table 4 here>

Second, in all cases except the full sample of the registered population, the estimated value of the exponent decreases over time, implying that large cities grew faster than small cities and that population gaps among cities increased. For the full sample of the registered population, the estimated value of Zipf exponent steadily increased in 1990–2000 and then decreased in 2000–2012. The increase in 1990–2000 may be caused by the increase in the number of cities (sample size). The number of cities grew from 188 in 1990 to 260 in 2012.

Third, the estimated value of the Zipf exponent using the permanent population is smaller than that using the registered population. The difference in the estimated Zipf exponent reveals that using the registered population shows a smaller population gap between different cities (sizes) than using the permanent population. I conclude that the difference is caused by the floating population moving disproportionately toward large cities and that the registered population underestimates the size of large cities.

Finally, the evidence for a divergent growth pattern is strongly present in large cities (Table 4). This is indicated by the decline of the Zipf exponent over time. For instance, for cities with a population of over half a million, the estimated exponent steadily dropped from 1.615 in 1990 to 1.432 in 2012 using the registered population and from 1.553 in 2000 to 1.232 in 2012 using the permanent population. The results using the sample of cities with a population of over one million are highly similar. This confirms the conclusion of divergent growth of large cities in China. The model performs well, as indicated by high R-square value, falling into the range of 0.896–0.996.

Table 5 reports the estimated results using Eq. (8). I choose two criteria for large cities: cities with a population of over one million and the top-50 largest cities. As expected, the dummy variable for large cities is significantly positive and different from zero, indicating that rank-size relationship for large cities is different from that for small cities. For large cities with a population of more than one million, the estimated coefficient for the dummy variable steadily dropped from 0.0963 in 1990 to 0.0199 in 2012 for the registered population and from 0.093 in 2000 to 0.064 in 2012 for the permanent population. Unlike the estimated value of α_2, there is no systematic pattern of change in the value of α_1 for both data sets although there is a tendency to increase for the registered population. For the top-50 largest cities, the estimated value of α_2 steadily declines over time for the permanent population but shows irregular changes over time for the registered population.[13] The results in Table 5 suggest that growth patterns of small cities are less clear after controlling for the growth pattern of large cities, which is divergent over time.

<Table 5 here>

2.7 Robustness Check

Testing for random growth or the validity of Gibrat's law amounts to testing for the presence of a unit root in city size. A number of recent papers adopt a panel unit

[13] I also estimate the Zipf exponent using a balanced sample that including 184 cities in existence through all years between 1990 and 2012. The results are highly similar to those from the full or unbalanced panel.

root test, which is suitable for data set with a short time dimension (Resende, 2004; Bosker et al., 2008; Schaffar & Dimou, 2012; González, et al., 2014). For a robustness check, this study applied panel unit root tests using both the registered population and permanent population for a balanced panel and large-city subsample and for both the entire period and breakdowns.

The general form for a panel unit root test is based on the Augmented Dickey-Fuller test, following Eq. (9):

$$\Delta lns_{it} = \emptyset_i lns_{i,t-1} + Z'_{it}\gamma_i + \sum_{j=1}^{P_i} \theta_{ij}\Delta lns_{i,t-j} + \epsilon_{it} \qquad (9)$$

where, s_{it} is relative city size. Z_{it} can include panel fixed effects and a time trend. $P_i$is the number of lagged city growth, which is determined by the Akaike information criterion (AIC).

In this study, I used two panel unit root tests (Levin-Lin-Chu test and Im-Pesaran-Shin test) to test the null hypothesis of all series with a unit root ($\emptyset_i$=0) versus the alternative of all or some of the series being stationary. The presence of a unit root implies a process of random growth and supports Gibrat's law of independence between growth and city size. On the other hand, the alternative implies that city growth depends on initial city size. The Levin-Lin-Chu test (LLC) assumes a common $\emptyset_i$ for all panels whereas the Im-Pesaran-Shin test (IPS) allows $\emptyset_i$ to vary across panels (Levin et al., 2002; Im et al., 2003).

Table 6 presents the results of panel unit root tests. The results of panel unit root tests are robust and strongly support the rejection of the random growth or Gibrat's law. As for the full balanced sample, both tests reject the null hypothesis of unit root for both the registered population and permanent population. Thus, city growth is significantly associated with city size during 1989-2012. As for the top-50 largest cities in the initial year, the growth in the permanent population of large cities is more significantly associated with city size than the growth in the registered population of large cities. Both tests reject Gibrat's law using the permanent population in 1999–2012, but only LLC test rejects Gibrat's law using the registered population in both 1989–2012 and 1999–2012. This is corresponding to previous findings that the registered population underestimates the growth of large cities as it does not include rural-urban migrants who are more likely to move to bigger cities.

<Table 6 here>

The comparison between the OLS rank-size regression using the registered population and that using the permanent population might be influenced by the differences in sample size. Thus, table 7 reports the comparison between the estimates of the OLS rank-size regression using the registered population and those using the permanent population for the same sample (same cities) in each year during the period of 2000–2012. The main conclusion still holds that the registered population underestimates the relative size and growth of large cities when compared with the permanent population, particularly in more recent years after 2002.

<Table 7 here>

Table 7-2 presents the estimates of the OLS rank-size regression for the balanced sample, including 184 cities that exist through all years during 1990 and 2012. The Zipf exponent is still always smaller using the permanent population than that using the registered population, implying that the registered population underestimates the relative size of large cities.

2.8 Final Remarks and Conclusion

The combination of radical reforms toward a market-oriented economy and remarkable pace of urbanization in China presents a great opportunity to examine the growth pattern of cities and the evolution of the city system. This paper applies a non-parametric analysis to investigate growth patterns of Chinese cities during rapid urbanization. The estimated results from non-parametric analysis first reject Gibrat's law and then reveal a complicated, non-linear relationship between city growth and city size. A U-shaped relationship between growth rate and city size indicates a convergent growth pattern for small cities and a divergent growth pattern for large cities. The conclusion of divergent growth of large cities is also supported by estimates of the local Zipf exponent and by the rank-size regression.

Although the results are different from others (Song & Zhang, 2002; Xu & Zhu, 2009; Chen et al., 2013), the conclusion about the divergent growth of large cities does not come with surprise. Similar to many other developing countries, large cities are preferred destinations of the rural-city migration during rapid urbanization in China (Moomaw & Shatter, 1996). Large cities have high amenities, attracting businesses, workers, and consumers. These amenities cover education, public health, infrastructure and transportation, and goods and services. Small cities cannot match up with large cities regarding those urban amenities in terms of both quality and quantity. Businesses and workers could achieve higher productivity in larger cities, and consumers may be more satisfied in larger cities. Moreover, the political significance of large cities in China further reinforces their growth.

The finding of the divergent growth of large cities has three profound policy implications. First, the national strategy of urbanization that specifically reversely links city growth with city size is against the general trend of development. Consequently, it is not surprising to observe that the strategy has had little effect on the growth of cities and on the evolution of the city system in China in the past couple of decades.

Second, the policy of strictly controlling the growth of mega and super-big cities makes these cities less prepared for growth potential driven by market forces and may cause them to choose inappropriate policy options. For instance, under the control policy of large cities, in 2004, Beijing planned a population growth ceiling of 18 million by 2020. This ceiling has been used to determine the provision of infrastructure and urban services. However, the population of Beijing based on official data had already reached 23 million in 2012, which is still widely believed to be underestimated. The mismatch of population growth and provision of infrastructure (such as urban transportation) and urban services partly explains the rapidly increasing congestion in Beijing.

Third and finally, the divergent growth of large cities in China may continue into the next one or two decades, even under the current national strategy of urbanization. Accordingly, large cities should prepare themselves to accommodate substantial population surges by providing more efficient infrastructure and urban services in order to promote sustainable growth.

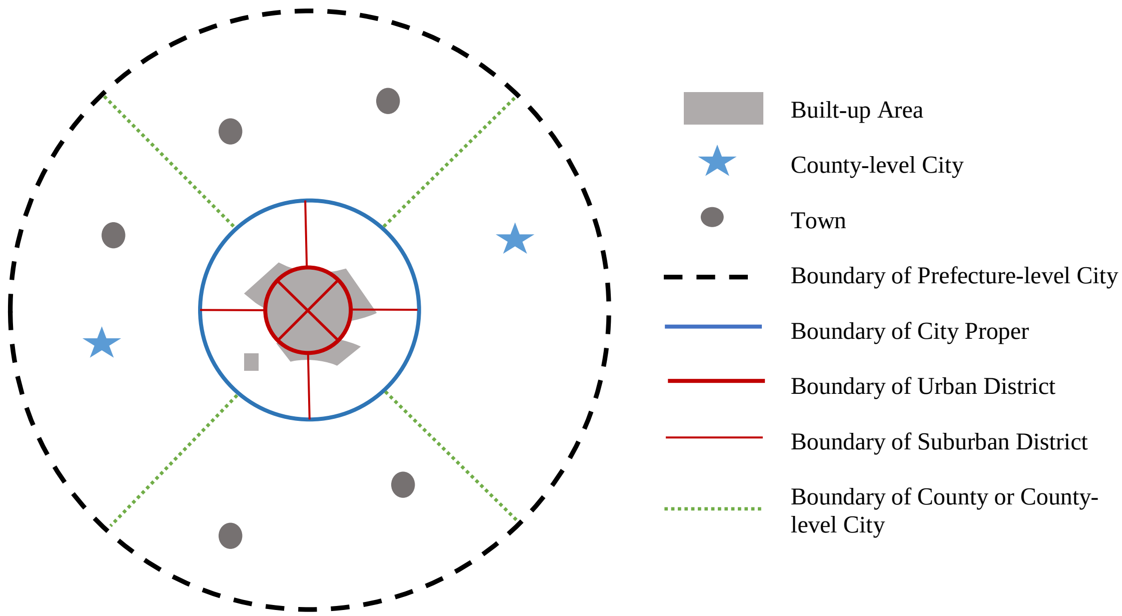
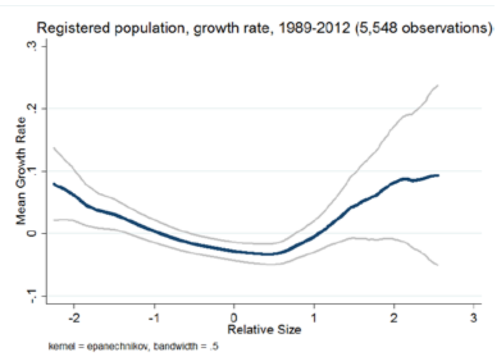
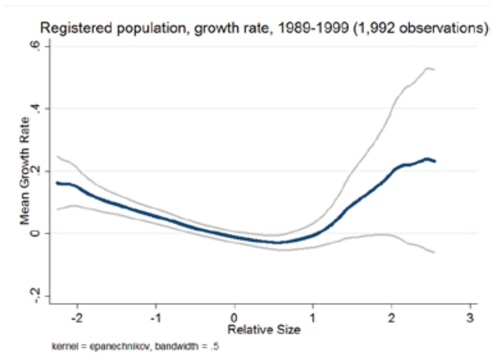


Figure 1. The City-Managing-County System

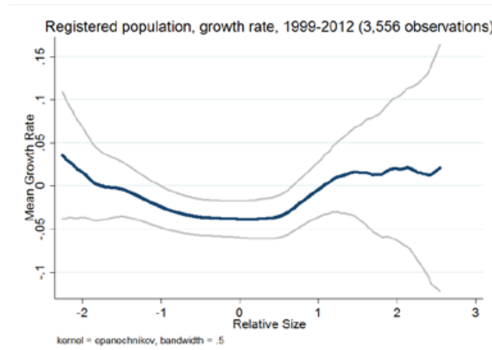
Registered population



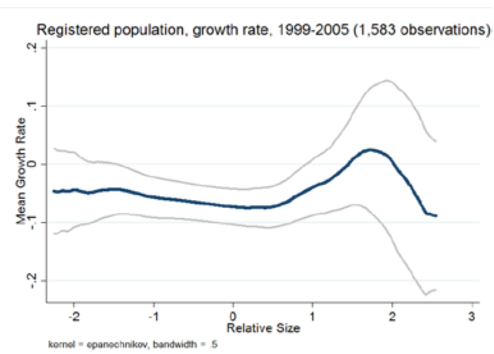
(a) 1989–2012



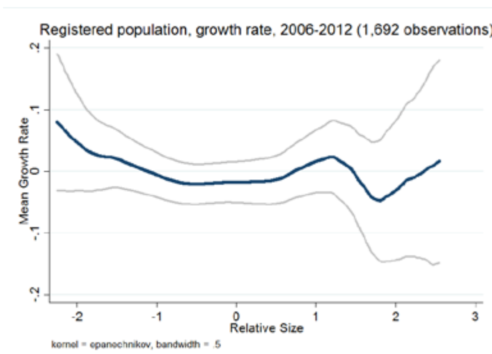
(b) 1989–1999



(c) 1999–2012

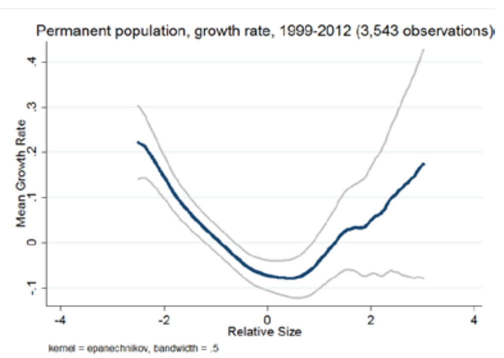


(d) 1999–2005

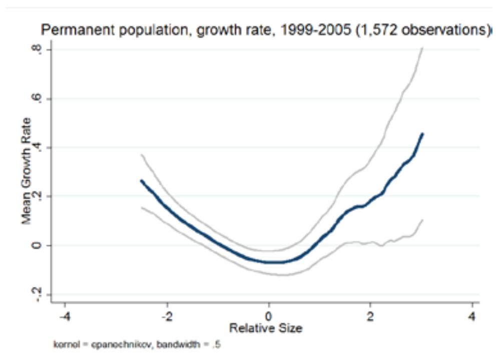


(e) 2006–2012

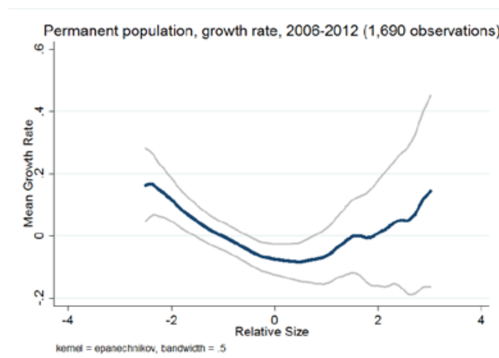
Permanent population



(f) 1999–2012



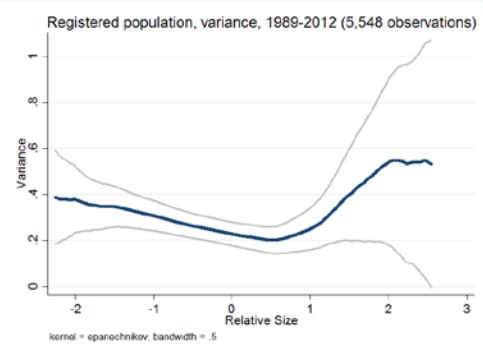
(g) 1999–2005



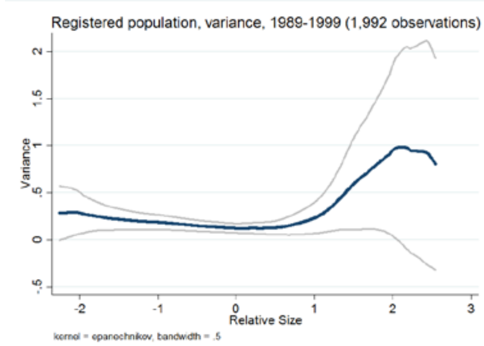
(h) 2006–2012

Figure 2. Non-parametric estimates of the mean growth rate conditional on city size

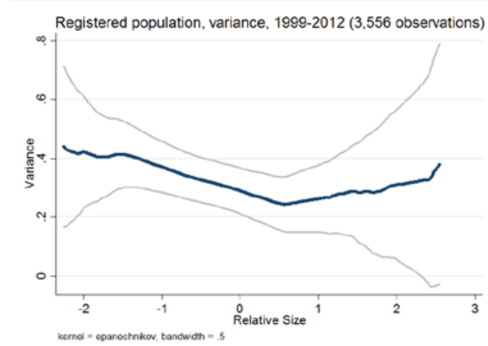
Registered population



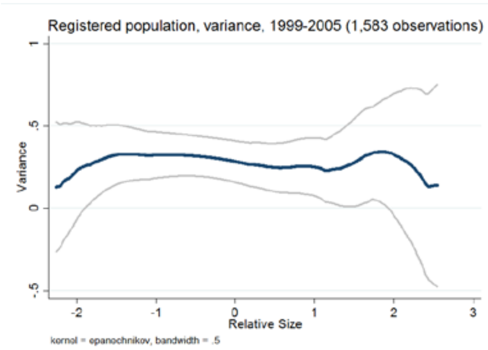
(a) 1989–2012



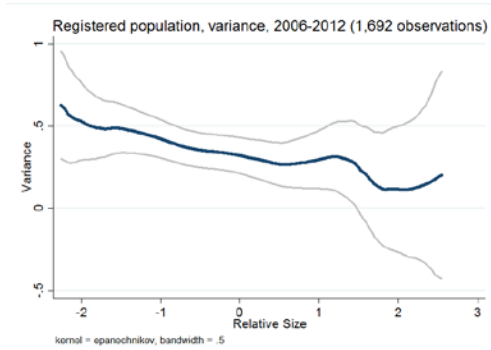
(b) 1989–1999



(c) 1999–2012

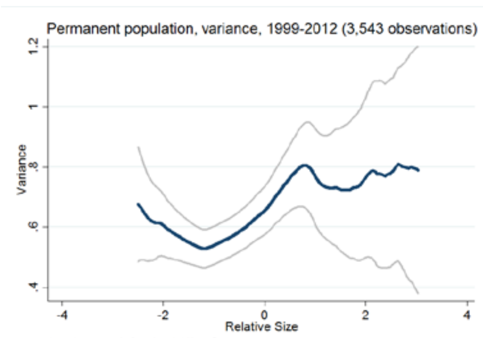


(d) 1999–2005

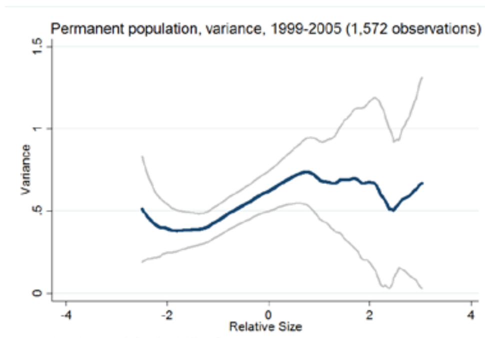


(e) 2006–2012

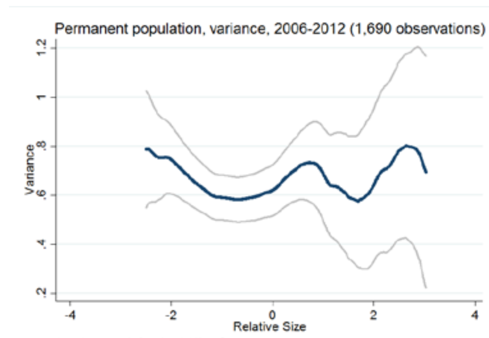
Permanent population



(f) 1999–2012



(g) 1999–2005



(h) 2006–2012

Figure 3. Non-parametric estimates of the variance of growth rate conditional on city size

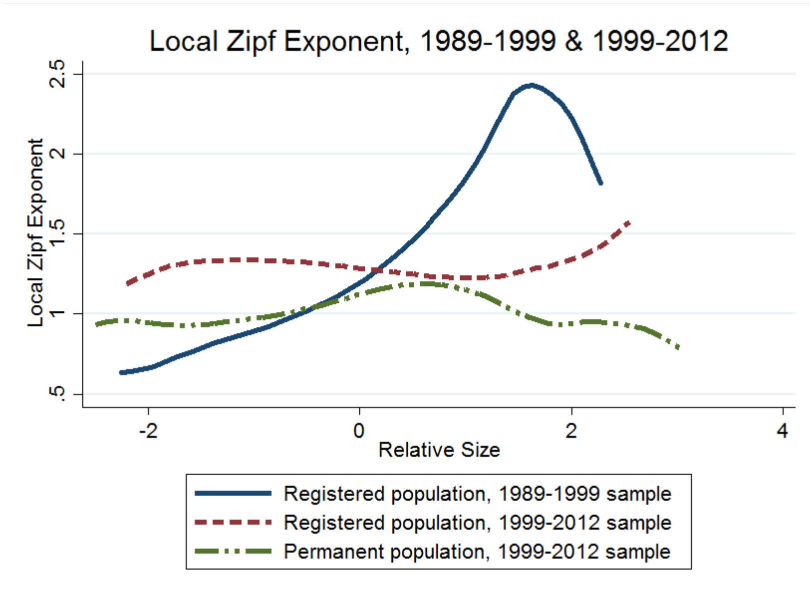


Figure 4. Non-parametric estimates of the local Zipf exponent

Table 1. Definition of urban population

<table>
<tr><td></td><td>China City Statistical Yearbook (1989–2012)</td><td colspan="2">China Urban Construction Statistical Yearbook (1999–2012)</td></tr>
<tr><td>Population</td><td>Total registered population</td><td colspan="2">Permanent population: total registered population + temporary population</td></tr>
<tr><td rowspan="2">Urban Area</td><td rowspan="2">City Proper: districts under the jurisdiction of a city</td><td>1999-2005</td><td>2006-2012</td></tr>
<tr><td>(1) Entire city districts, if districts population density > 1,500/km²;
(2) Only the areas administered by statutory street committee, if district population density < 1,500/km²;
(3) Other areas connected to city public facilities, residential facilities and municipal facilities;
(4) Special settlement[14]</td><td>(1) Areas administered by statutory neighborhood office;
(2) Other areas directly[15] connected to city public facilities, residential facilities and municipal facilities;
(3) Special settlement</td></tr>
</table>

[14] Special settlement refers to independent industrial and mining districts, development zones, research institutes, universities, colleges with over 3,000 permanent residents.
[15] "Directly connected" means facilities are not cut off by non-construction land such as water areas, agriculture land, parks, woodland or pasture.

Table 2. Descriptive statistics of Chinese cities at prefecture level or above, 1989–2012

	Year	Obs.	Mean	Median	Skewness	Min.	Max.	Standard deviation
Total registered population in the city proper	1999	234	110.6	73.61	4.82	14.55	1127.2	135
	2000	260	109.4	75.03	4.81	15.96	1136.8	132
	2001	265	114.4	77.44	4.83	16.1	1262.4	139.05
	2002	275	118.8	78.64	4.66	14.29	1270.2	145.32
	2003	282	120.9	80.2	4.54	14.08	1278.2	147.07
	2004	284	122.7	81.88	4.5	14.35	1289.1	148.71
	2005	284	127	82.32	4.26	14.62	1290.1	154.1
	2006	284	128.5	85.29	5.06	14.93	1511	161.58
	2007	284	130	85.35	5.04	15.3	1526	163.51
	2008	285	131.1	87.52	5.04	15.33	1534.5	164.77
	2009	286	133.1	88.4	5.01	15.33	1542.8	166.11
	2010	285	136.1	88.95	4.87	15.23	1542.8	168.83
	2011	287	138.7	90.5	5.26	15.3	1770.6	176.87
	2012	287	140.5	91	5.17	15.1	1779.1	179.12
Permanent population in urban area	Year	Obs.	Mean	Median	Skewness	Min.	Max.	Standard deviation
	1999	234	103.7	69.2	4.68	9.05	1127.2	120.86
	2000	259	102.4	68	4.62	9.85	1136.8	122.3
	2001	265	109.3	71.39	4.69	10.67	1262.4	145.84
	2002	272	109.7	67.11	4.92	1.78	1292.2	147.84
	2003	280	107.3	59.03	4.59	8.8	1312.7	160.43
	2004	281	110.3	57.58	4.7	11	1528.5	173.78
	2005	282	117.9	57.01	5.53	11	1893	210.31
	2006	284	106.1	54.67	5.5	10.4	1815.1	185.28
	2007	284	105.8	54.74	5.61	11.3	1858.1	191.96
	2008	285	105.1	55.97	5.75	11.3	1888.5	184.23
	2009	286	106.4	57.15	5.88	10.6	1921.3	185.95
	2010	285	112.2	58.73	6.51	12.04	2301.9	209.99
	2011	287	116.2	61.42	6.41	13.03	2347.5	216.57
	2012	287	120.2	61.35	6.29	12.98	2380.4	221.3

Table 3. OLS estimates of rank-size (Zipf) exponent, full sample

Full Sample								
	Registered population				Permanent population			
Year	α	Standard Error	R^2	N	α	Standard Error	R^2	N
1990	1.196	0.03	0.896	188				
1992	1.223	0.029	0.904	191				
1994	1.24	0.029	0.898	204				
1996	1.234	0.027	0.906	216				
1998	1.271	0.025	0.921	227				
2000	1.316	0.022	0.932	260	1.152	0.024	0.898	259
2002	1.251	0.021	0.928	275	1.032	0.023	0.881	272
2004	1.225	0.021	0.923	284	1.024	0.015	0.945	281
2006	1.22	0.021	0.922	284	1.018	0.014	0.949	284
2008	1.212	0.021	0.92	285	1.056	0.013	0.956	285
2010	1.225	0.02	0.928	285	1.056	0.013	0.959	285
2012	1.206	0.02	0.926	287	1.059	0.012	0.962	287

Table 4. OLS estimates of rank-size (Zipf) exponent, truncated sample

	Cities (>0.5 million)								Large cities (>1 million)							
	Registered population				Permanent population				Registered population				Permanent population			
Year	α	Standard Error	R^2	N	α	Standard Error	R^2	N	α	Standard Error	R^2	N	α	Standard Error	R^2	N
1990	1.615	0.03	0.977	125					1.836	0.029	0.986	62				
1992	1.62	0.029	0.981	129					1.835	0.028	0.987	61				
1994	1.636	0.029	0.978	141					1.879	0.023	0.99	72				
1996	1.598	0.027	0.975	148					1.856	0.025	0.987	78				
1998	1.57	0.025	0.976	162					1.775	0.029	0.978	84				
2000	1.574	0.022	0.977	191	1.553	0.019	0.982	173	1.731	0.033	0.969	90	1.783	0.019	0.991	84
2002	1.512	0.021	0.983	209	1.425	0.016	0.981	174	1.688	0.018	0.989	101	1.651	0.016	0.993	88
2004	1.5	0.021	0.981	217	1.276	0.022	0.988	157	1.675	0.016	0.99	107	1.377	0.022	0.982	73
2006	1.484	0.021	0.98	221	1.255	0.018	0.992	152	1.666	0.014	0.991	117	1.35	0.018	0.988	67
2008	1.464	0.021	0.979	230	1.253	0.021	0.992	154	1.66	0.013	0.992	121	1.314	0.021	0.985	62
2010	1.451	0.02	0.98	234	1.249	0.015	0.996	166	1.643	0.013	0.992	125	1.29	0.015	0.991	68
2012	1.432	0.02	0.98	235	1.232	0.016	0.995	172	1.626	0.011	0.994	127	1.276	0.016	0.989	76

Table 5. OLS estimates of rank-size (Zipf) exponent, large city dummy

	Large city dummy=1: urban population>1 million								Large city dummy=1: top 50 largest cities							
	Registered population				Permanent population				Registered population				Permanent population			
Year	α_1	α_2	R^2	N	α_1	α_2	R^2	N	α_1	α_2	R^2	N	α_1	α_2	R^2	N
1990	0.944***	0.0963***	0.92	188					0.889***	0.128***	0.93	188				
	(0.047)	(0.015)							(0.038)	(0.013)						
1992	0.972***	0.0945***	0.92	191					0.921***	0.123***	0.94	191				
	(0.045)	(0.014)							(0.040)	(0.010)						
1994	1.015***	0.0809***	0.91	204					0.916***	0.134***	0.94	204				
	(0.049)	(0.014)							(0.036)	(0.011)						
1996	1.057***	0.0631***	0.91	216					0.923***	0.132***	0.95	216				
	(0.048)	(0.014)							(0.032)	(0.011)						
1998	1.126***	0.0499***	0.93	227					0.964***	0.129***	0.96	227				
	(0.045)	(0.013)							(0.028)	(0.009)						
2000	1.152***	0.0560***	0.94	260	0.916***	0.0931***	0.92	259	1.016***	0.129***	0.97	260	0.848***	0.151***	0.95	259
	(0.039)	(0.011)			(0.039)	(0.013)			(0.023)	(0.008)			(0.025)	(0.009)		
2002	1.098***	0.0537***	0.93	275	0.789***	0.105***	0.91	272	0.971***	0.126***	0.96	275	0.749***	0.155***	0.94	272
	(0.037)	(0.011)			(0.036)	(0.013)			(0.023)	(0.008)			(0.025)	(0.010)		
2004	1.068***	0.0559***	0.93	284	0.852***	0.0787***	0.96	281	0.945***	0.130***	0.96	284	0.837***	0.0990***	0.96	281
	(0.037)	(0.011)			(0.024)	(0.009)			(0.023)	(0.008)			(0.020)	(0.008)		
2006	1.106***	0.0396***	0.93	284	0.847***	0.0818***	0.96	284	0.941***	0.129***	0.96	284	0.844***	0.0928***	0.97	284
	(0.040)	(0.010)			(0.020)	(0.010)			(0.023)	(0.008)			(0.019)	(0.008)		
2008	1.110***	0.0357***	0.92	285	0.892***	0.0773***	0.97	285	0.935***	0.129***	0.96	285	0.900***	0.0794***	0.97	285
	(0.039)	(0.011)			(0.021)	(0.008)			(0.024)	(0.008)			(0.020)	(0.008)		
2010	1.166***	0.0203*	0.93	285	0.892***	0.0749***	0.97	285	0.962***	0.119***	0.96	285	0.898***	0.0796***	0.97	285
	(0.038)	(0.011)			(0.021)	(0.008)			(0.024)	(0.008)			(0.019)	(0.008)		
2012	1.148***	0.0199*	0.93	287	0.913***	0.0640***	0.97	287	0.946***	0.119***	0.96	287	0.910***	0.0745***	0.97	287
	(0.037)	(0.011)			(0.021)	(0.008)			(0.023)	(0.008)			(0.018)	(0.007)		

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6. Robustness check: Panel Unit Root Tests

	Unit Root Test statistics	Full balanced panel 1989-2012 (184 cities)	1989-1999 (184 cities)	1999-2012 (232 cities)
Registered population	LLC test	-6.1563*	-48.0074*	-210*
	IPS test	-3.7662*	-65.1856*	-31.182*
Permanent population	LLC test			-92.3757*
	IPS test			-21.8953*
	Unit Root Test statistics	**Top 50 1989-2012**	**1989-1999**	**1999-2012**
Registered population	LLC test	-3.1311*	-5.6591*	-37.2071*
	IPS test	-0.6679	-9.0986*	-0.4839
Permanent population	LLC test			-65.9907*
	IPS test			-17.4405*

Note: *indicates rejection of unit root at 1 per cent level. Both tests include a time trend and panel means.

Table 7. Robustness check: rank-size OLS regression, same sample

Table 7-1

Full Sample								
	Registered population				Permanent population			
Year	α	Standard Error	R^2	N	α	Standard Error	R^2	N
2000	1.314	0.022	0.932	259	1.152	0.024	0.898	259
2002	1.265	0.02	0.934	272	1.032	0.023	0.881	272
2004	1.241	0.021	0.928	281	1.024	0.015	0.945	281
2006	1.22	0.021	0.922	284	1.018	0.014	0.949	284
2008	1.212	0.021	0.92	285	1.056	0.013	0.956	285
2010	1.225	0.02	0.928	285	1.056	0.013	0.959	285
2012	1.206	0.02	0.926	287	1.059	0.012	0.962	287
Medium-size and large cities (>0.5 million)								
	Registered population				Permanent population			
Year	α	Standard Error	R^2	N	α	Standard Error	R^2	N
2000	1.523	0.018	0.976	173	1.553	0.016	0.982	173
2002	1.411	0.019	0.971	174	1.425	0.015	0.981	174
2004	1.382	0.019	0.97	158	1.275	0.011	0.988	158
2006	1.365	0.02	0.969	152	1.255	0.009	0.992	152
2008	1.333	0.023	0.958	154	1.253	0.009	0.992	154
2010	1.367	0.022	0.961	166	1.249	0.007	0.996	166
2012	1.345	0.021	0.959	172	1.232	0.007	0.995	172
Large cities (>1 million)								
	Registered population				Permanent population			
Year	α	Standard Error	R^2	N	α	Standard Error	R^2	N
2000	1.6	0.042	0.946	84	1.783	0.019	0.991	84
2002	1.584	0.021	0.985	88	1.651	0.016	0.993	88
2004	1.456	0.025	0.979	73	1.377	0.022	0.982	73
2006	1.421	0.029	0.973	67	1.35	0.018	0.988	67
2008	1.486	0.028	0.979	63	1.31	0.021	0.984	63
2010	1.411	0.033	0.965	68	1.29	0.015	0.991	68
2012	1.416	0.03	0.968	76	1.276	0.016	0.989	76

Table 7-2

	Balanced sample (184 cities)							
	Registered population				Permanent population			
Year	α	Standard Error	R^2	N	α	Standard Error	R^2	N
1990	1.208	0.029	0.904	184				
1992	1.227	0.028	0.911	184				
1994	1.238	0.028	0.913	184				
1996	1.236	0.027	0.918	184				
1998	1.239	0.025	0.93	184				
2000	1.237	0.023	0.94	184	1.207	0.024	0.931	184
2002	1.187	0.023	0.934	184	1.131	0.023	0.933	184
2004	1.182	0.024	0.929	184	1.059	0.018	0.95	184
2006	1.177	0.025	0.927	184	1.059	0.018	0.953	184
2008	1.182	0.024	0.928	184	1.08	0.016	0.961	184
2010	1.17	0.024	0.927	184	1.065	0.015	0.964	184
2012	1.15	0.024	0.926	184	1.064	0.015	0.963	184

Chapter 3: Agglomeration Economies and Regional Industrial Dominance in China: An Analysis of Firm-level Productivity

3.1 Abstract

Using 2007 plant-level data in China, this study investigates whether the effects of agglomeration economies vary with industries and whether regional industrial dominance diminishes plant-level productivity through limiting agglomeration economies. The cross-sectional analysis suggests that the mechanisms of agglomeration economies vary with industry groups. More specifically, knowledge spillover effects and a more diverse and large urban environment are more important for the high-tech industry, while the traditional light industry mainly benefits from a more specialized urban environment. The traditional heavy industry is found to mainly benefit from the general advantage of a large urban environment. Regional industrial dominance has both direct and indirect negative effects on plant-level productivity. A highly concentrated industrial structure in a city would diminish productivity of firms in the same industry and same city by limiting localization economies, particularly for small plants. However, a large and diverse urban environment may mitigate the negative effects of regional industrial dominance, as firms may turn to alternative externalities from other industries. The conclusion is substantiated by further investigation on the differences in the ownership of dominant firms. The results have profound policy implications on how to create regional/local economic environments to make the best of agglomeration economies to promote productivity growth for different types of industries.

3.2 Introduction

Using 2007 firm-level manufacturing survey data in China, this paper attempts to fill the void by re-investigating the productivity effects of agglomeration economies, with a focus on how regional industrial dominance limits a firm's ability to capture the benefits of agglomeration economies and diminishes firm productivity.

By comparing New York with Pittsburgh (Chinitz, 1961) and Silicon Valley with Route 128 (Saxenian, 1994), case studies first reported that a region dominated by a few large firms in an industry would generate fewer positive externalities associated with agglomeration economies, ultimately diminishing productivity and obstructing entrepreneurship and innovation. However, while empirical studies found that plants would have lower productivity in regions where their own industry is dominated by a few large firms (Feser et al., 2002; Drucker & Feser, 2012), it still lacks generalized empirical evidence supporting the view that agglomeration economies are the mediating mechanism for the negative impact of regional industrial dominance on firms' productivity.

In addition, this study quantifies the relative importance of various sources and types of agglomeration economies, focusing on differences across different categories of industry types. Thus, this study also directly contributes to the empirical debate on how agglomeration mechanisms differ across industries and whether a firm benefits from locating near other firms in the same industry (localization economies) or from locating near firms in other different industries (urbanization economies).

Despite the academic significance, this study is also particularly relevant to the economic development and industrial policy in the context of China. Since 2010, China has been the largest manufacturing economy in the world, taking the place of the United States. However, the labor productivity and manufacturing intensity per capita are still relatively low compared with more industrialized countries. Meanwhile, manufacturing enterprises in China are facing challenges associated with rising labor costs, resource depletion, currency appreciation, and more rigorous application of environmental protection and patent protection laws (Hu & Sun, 2014; Hu et al., 2015). If China wants to maintain its sustainability of competitiveness, the on-going industrial transformation and upgrading should focus on productivity improvement and innovation. Agglomeration economies, referring to the external benefits firms received from co-locating with each other, have been regarded as a primary source for enhancing productivity and promoting innovative activity (Rosenthal & Strange, 2004).

However, empirical studies only provide limited and mixed evidence on the productivity gains of industrial agglomeration in China. For example, Mody and Wang (1997) and Batisse (2002) reported a negative relationship between industrial specialization and regional industrial growth, whereas Fan and Scott (2003) and Ke (2010) found industrial agglomeration enhances regional productivity. At the firm level, Lin et al. (2011) and Yang et al. (2013) found a positive relationship between industrial agglomeration and firms' productivity for the textile industry and electronics industry, while Hu et al. (2015) argued that congestion and competition offset the benefits of industrial agglomeration within the same industry by looking across a comprehensive range of industries.

These inconsistent results might be attributed to two reasons. First, they fail to recognize that different industries might be affected by agglomeration economies in different ways. Second, the interaction effects between industrial structure and agglomeration economies are largely unexplored. By addressing these two issues, this study offers policymakers a better understanding of how to create regional/local economic environments to make the best of agglomeration economies to promote productivity growth for different types of industries.

China also presents a unique setting to study this topic, as its economic environments are substantially different from those in the western, developed countries. First, China is still in transition from a centrally-planned economy to a market-oriented economy. Compared to the U.S. economy, overall industrial concentration is lower in China (Lu & Tao, 2009), and the domestic market is fragmented (Young, 2000; Poncet, 2003). In addition, besides market forces, industrial agglomeration in China is also strongly influenced by public policies. For example, Yang et al. (2013) argued that the policy-directed agglomeration of the high-tech industries in China is mainly driven by the establishment of national science & technology industrial parks, whereas industrial agglomeration in the United States mainly relies on the market forces, such as the formation of Silicon Valley and Route 128.

Second, the negative effect of regional industrial dominance on agglomeration economies and productivity may be more significant in China, because local dominant firms can enjoy a significantly higher degree of local protectionism, a factor that may further retard agglomeration economies and diminish productivity (Porter, 1998). Unlike the United States where interregional trade barriers are strictly prohibited, local protectionism is an important factor in obstructing industrial agglomeration in China (Bai et al., 2004; Lu & Tao, 2009). After the 1994 fiscal reform, local governments in

China can share tax revenues with the central government, leading to strong incentives to protect local firms, especially the large and dominant ones, in order to maximize local fiscal revenues and avoid massive layoffs (Poncet, 2005). Thus, a higher degree of local monopoly or industrial structure concentration may be significantly associated with a higher degree of local protectionism, further lowering the level of agglomeration economies and productivity.

Third, Chinese firms' different ownership structures (state-owned enterprise, foreign-invested enterprise, private enterprise) would further complicate the impact of agglomeration economies and industrial structure on productivity. The performances of Chinese firms differ considerably across their ownership structures, which also shape a firm's ability to influence and benefit from agglomeration economies (Lin et al., 2011; Hu et al., 2015). Thus, it is also possible that the ownership of a dominant firm can also shape its influence on agglomeration economies and the productivity of other firms. So far, no studies have ever investigated this issue.

The dataset comes from 2007 China Annual Survey of Manufacturing Firms collected by the National Bureau of Statistics at firm level. Compared with previous studies on agglomeration in China, this study has three advantages. First, industries are classified into three groups, including the high-tech industry, the traditional light industry, and the traditional heavy industry, in order to provide quantitative evidence on how different industry groups are subject to different types and sources of agglomeration economies and how the effects of regional industrial dominance vary with industry categories.

Second, following the benchmark study (Drucker & Feser, 2012), regional industrial dominance is directly measured as a three-firm concentration ratio, which is the share of total industrial output made by the three largest firms for a three-digit industry in a city. I also calculate the share of total industrial output made by the largest state-owned enterprise (SOE), the largest private enterprise (PE), and the largest foreign-invested enterprise (FIE), separately, for each three-digit industry in a city, in order to understand how the effect of the dominance of the largest firm varies with different firm ownerships.

Third, this study tries to create proxies that distinguish among different types and sources of agglomeration economies. Based on Henderson (2003), the count of employment would reflect the degree of labor market pooling, and the count of firms is more related to the knowledge spillover effects. In this study, hence, with a focus on labor market pooling, localization economies are measured by the own-industry neighboring employment, while urbanization economies are measured by the related-industry and other-industry employment. In contrast, with a focus on knowledge spillover, localization economies are measured by the count of own-industry firms while urbanization economies are measured by the count of firms in the related industries and other industries.

By estimating the production function, a cross-sectional analysis on 2007 firm-level data in China provides evidence that the industrial dominance in a city has both a direct negative influence on firm-level productivity and an indirect negative effect through limiting externalities of localization economies, particularly for small manufacturing plants. The results lend support for Chinitz (1961) and Saxenian (1994) and are partially consistent with Drucker and Feser (2012), who do not discover significantly indirect effects of regional industrial dominance. The analysis also shows that the negative effect of regional industrial dominance on firms' productivity may be mitigated in a large and diverse urban environment.

Further investigation on the ownership of dominant firms substantiates the main findings. The results show that values of the concentration ratio of the largest SOE, the largest PE and the largest FIE in a city are all associated with lower productivity of other firms, except that a dominant SOE in a city has insignificant effect on other firms' productivity in the traditional light industry. While a dominant private firm is found to enhance the positive effect of localization economies in the traditional light industry, regional industrial dominance seems to results in fewer positive externalities of localization economies for all other cases.

The results also suggest that mechanisms of agglomeration economies vary with industry groups. More specifically, knowledge spillover effects and a more diverse and large urban environment (urbanization economies) are more important for the high-tech industry, and the traditional light industry mainly benefits from a more specialized urban environment, particularly the own-industry labor market pooling and the concentration of related-industry activities. The results lend support for the product life-cycle location theory, which indicates that while innovative and young industries rely more on urbanization economies, standardized and mature industries benefit more from localization economies (Duranton and Puga, 2001). Surprisingly, the traditional heavy industry is reported to mainly benefit from urbanization economies, in line with

Feser (2001) and Ehrl (2013) but in contrast to the findings of Henderson et al. (1995), Henderson et al. (2001) and Lee et al. (2010).

The paper is organized as follows. Section 3.3 provides an overview of the related literature, which is followed by data and methodology in section 3.4. Section 3.5 presents empirical findings and results. Section 3.6 gives final conclusion and policy implications.

3.3 Literature

3.3.1 Theory

Since the effect of regional industrial structure on firm's performance is associated with externalities among firms, the theory of agglomeration economies provides the theoretical foundation for this study. Agglomeration economies generate positive externalities to lower production costs, increase productivity, and promote innovation mainly through three individual sources: intermediate input sharing, labor market pooling, and knowledge spillover (Krugman, 1991). A pooled labor market could generate better matching between workers and employers, lower cost of searching and training workers, and improve the flow of workers between firms. Input sharing enables the production of specialized intermediate inputs, and, hence, supplier industries could provide cheaper inputs due to scale economies. Proximity also enables interaction among firms and workers, increasing sharing of knowledge and skills and generating new ideas. While large firms could achieve a higher level of scale economies within the firm, agglomeration economies allow small firms to compensate for their disadvantages by creating a more competitive industrial structure, which is an alternative to oligopoly and exhibits a higher degree of vertical disintegration and specialization (Carree & Thurik, 1999).

The oldest debate on agglomeration economies concerns the relative importance of two types of agglomeration economies: localization economies and urbanization economies (Rosenthal & Strange, 2004). Marshall-Arrow-Romer (MAR) externalities, or localization economies, recognize the importance of the concentration of economic activities within the same industry and suggest that firms would mainly benefit from co-locating with other firms in the same industry (Marshall, 1890; Arrow, 1962; Romer, 1986). In contrast, Jacobs (1969) believes co-locating with firms in other industries or industrial diversity would enhance productivity and promote innovation through cross-fertilization. The benefits of co-locating with firms in other different industries refer to urbanization economies. In general, the product life-cycle location theory indicates that new products are developed in a diversified environment whereas standardized production of mature products relocates to specialized areas, implying that while innovative and young industries rely more on urbanization economies, standardized and mature industries benefit more from localization economies (Duranton & Puga, 2001).

In the framework of agglomeration economies, recent theoretic work focuses on how industrial structure or business culture influences the degree to which a given pattern of agglomeration enhances productivity or promotes innovation (Chinitz, 1961; Saxenian, 1994; Rosenthal & Strange, 2004). For example, with a focus on localization economies, Porter (1990) argues that local competition, as opposed to local monopoly, promotes knowledge spillover and innovation. While regional industrial structure concentration can affect firm performance through several channels, such as increasing entry barriers or reducing entrepreneurial activities and the availability of capital and investment for small firms (Chinitz, 1961; Booth 1986; Glaeser & Kerr, 2009), this study focuses on the mechanism directly related to the sources of agglomeration economies. There are three mechanisms by which regional industrial dominance would diminish firms' performance through limiting agglomeration economies.

First, regional dominance of a few large firms in an industry would reduce intermediate input sharing. Large dominant firms often exhibit higher levels of vertical integration and their services are often unavailable to outsiders, because they can achieve scale economies within the firm (Chinitz, 1961; Porter, 1998). Thus, a concentrated industrial structure is characterized as increasing returns that are internal to large firms instead of being external to any single firm (Enright, 1995). The availability of input would be also limited if an industry is dominated by a few large firms, because suppliers often prefer large volume contracts with large firms and are more responsive to the needs of large dominant firms than to the needs of small firms (Booth, 1986). In addition, the high demand for intermediate inputs by dominant firms might raise the costs of intermediate inputs for smaller firms (Lee et al., 2010).

Second, labor pooling and the flow of workers among firms might also be reduced, because high-quality workers can be easily attracted to large dominant firms, which are more stable and provide better welfare and relatively secure, well-paying opportunities (Booth, 1986; Audretsh, 2001).

Third, a concentrated industrial structure would limit the networking and learning among firms, reducing both knowledge spillover effects and innovative activities (Chinitz, 1961; Saxenian, 1994). Large dominant firms are more vertically integrated, which decreases the face-to-face contact across firms (Enright, 1995). If an industry is dominated by a few large inward-looking firms in a region, all other firms may also suffer from lack of flexibility and be insensitive to innovation (Porter, 1998). A concentrated industrial structure would also limit entrepreneurship (Chinitz, 1961), which further retards the generation of new products and technologies, since small firms are the major sources of innovation and industrial evolution (Acs, 1992; Audretsch, 2001).

3.3.2 Empirical Evidence on the Nature and Sources of Agglomeration Economies

While there is an extensive body of literature suggesting positive productivity gains from agglomeration economies in general (Melo et al., 2009), empirical research has attempted to sort out the relative importance of different types and sources of agglomeration economies, but the results are mixed and vary dramatically across industries.

While some empirical evidence is more favorable to urbanization economies (Glaeser et al., 1992), most studies find stronger evidence of localization economies. For example, focusing on dynamic externalities in the United States, Henderson (1997) used panel data for five capital goods industries and discovered that the largest effects on productivity are from localization economies (own-industry employment) at two to five years in the past. In his more recent study, using U.S. plant-level data, Henderson (2003) found evidence of localization economies for the high-tech industry but not in the machinery industry, and the results suggested little evidence of urbanization economies in both industries. By examining the impact of agglomeration economies on the birth of new establishments in the United States for six industries, Rosenthal and Strange (2003) also found stronger evidence of localization economies. Similar results have also been obtained in other countries. For example, Lall et al. (2004) examined the effects of agglomeration economies on the plant-level productivity by jointly estimating the plant-level production function and cost share function in India. They found that while market access has a significantly positive effect on productivity in four industry sectors, localization economies are more important in two industry sectors and urbanization economies do not show significant impact on any industry sectors.

Another related empirical topic considers the pattern of how the productivity effect of localization economies and urbanization economies differs across industries. The conventional wisdom supports the product life-cycle location theory that localization economies or specialization have a positive effect on productivity of low-tech industries and mature firms, and urbanization economies or diversity are more important for high tech industries or new firms (Duranton & Puga, 2001; Rosenthal & Strange, 2004). However, empirical studies provide mixed results.

Most studies lend support for the product life-cycle location theory. For example, Henderson et al. (1995) examined eight U.S. manufacturing industries and found evidence of localization economies for mature capital goods industries and both localization economies and urbanization economies for high-tech industries. The results suggest that industrial diversity is important for attracting new industries but specialization is the key for business retention. A similar pattern has been obtained in other countries. Focusing on manufacturing industries in Japan, Nakamura (1985) found heavy manufacturing industries mainly benefit from localization economies, and urbanization economies are more important for light manufacturing industries. In studies on labor productivity using the plant-level data in Korea, Henderson et al. (2001) found evidence of localization economies in every industry, but urbanization economies (diversity) only have significant impact on labor productivity in the high-tech industry. Lee et al. (2010) also found that Korean mature industries mainly benefit from localization economies and that traditional light industries benefit from both localization and urbanization economies. Lee et al. (2010) also found that while localization economies or specialization have a significant impact for relatively old industries and large establishments, relatively young industries and small establishments mainly benefit from urbanization economies or diversity.

However, some studies find evidence that contradicts the conventional notion. For example, using U.S. data, Feser (2001) discovered that localization economies (own-industry employment) have significantly positive influence in the high-tech measuring and controlling devices sector, whereas urbanization economies (total population) have significant impact in the low-tech farm and garden machinery industry. One possible interpretation based on Feser (2001) is that high-tech or knowledge-intensive industries require more specialized infrastructure, equipment and labor, thus benefiting more from localization economies or specialization. In contrast, low-tech industries only require workers with less specialized skills and produce less knowledge-intensive goods, and therefore these industries mainly benefit from general advantages of large urban environments.

In addition, studies also find that the effects of agglomeration economies differ widely across regions. For example, Marrocu et al. (2013) found that the productivity of knowledge-intensive service sector is enhanced by specialization in old mature countries of Europe but is promoted by diversity in new developing countries of Europe. Regarding the effect of specialization on the productivity of low-tech manufacturing sectors, Marrocu et al. (2013) found negative effects in old mature countries but positive effects in new developing countries.

Instead of focusing on types of agglomeration economies, several recent studies specify explicit individual sources of Marshallian agglomeration economies and investigate how industry sectors benefit from these sources differently. In general, labor market pooling is often reported to have the greatest impact on productivity at the aggregated level (Baldwin et al., 2010; Ehrl, 2013).

Nevertheless, agglomeration mechanisms differ substantially among plants and industries. Focusing on startups in the United States at the city-industry level, Glaeser and Kerr (2009) found that labor pooling has consistent influence throughout the entry-size distribution, the effects of knowledge spillover appear most important for small startups, and input/output strength is more important for attracting larger entrants. Feser (2002) examined the impact of different sources of agglomeration economies on the establishment-level productivity for two U.S. manufacturing sectors. While both sectors benefit from the proximity to producer services, the results show that labor market pooling and knowledge spillover from university research are more important for the innovation-intensive measuring and controlling devices sector, and that the access to input supplies and knowledge spillover from applied innovation enhance the productivity in the low-tech farm and garden machinery industry. Ehrl (2013) investigated the impact of different sources and types of agglomeration economies on

TFP using German establishment- and employment-level data from 2000 to 2007 and found that the high-tech sector benefits from knowledge spillover and diversity, labor market pooling is more important for medium-tech industries, and knowledge spillover matters most for low-tech industries. Similarly, Henderson (2003) argued that high-tech industries in the United States mainly benefit from knowledge spillover (the count of their own-industry plants) rather than from labor market pooling (their own-industry employment). Focusing on Canadian manufacturing plants, Baldwin et al. (2010) discovered that labor market pooling is more important for scale-based, product-differentiated, and science-based sectors, the density of upstream suppliers is more important for natural resource-based, labor-intensive, scale-based industries, and knowledge spillover has larger influence in scale-based and science-based sectors.

3.3.3 Empirical Evidence on Industrial Structure and Agglomeration Economies

The above discussion suggests that the effects of agglomeration economies vary widely across industry sectors and locations, which stresses location- and industry-specific influences on the productivity effects of agglomeration economies. Indeed, case studies report that the concept of agglomeration economies is not enough to explain the differences in the economic performance of two regions, both of which exhibit high levels of industrial agglomeration. It is the fundamental differences in regional industrial structure that influence the degree to which agglomeration economies generate positive externalities and enhance firms' performance. More specifically, agglomeration economies would create greater external economies under a competitive industrial structure, and a concentrated industrial structure or regional industrial dominance would diminish firms' performance through limiting agglomeration economies.

Chinitz (1961) is the first study to point towards the need to examine the degree of regional industrial dominance, which would yield fewer agglomeration economies compared to a competitive industrial structure. The case study argued that New York is much more entrepreneurial than Pittsburgh because of the presence of a large number of small firms in New York and the domination by a few large integrated steel firms in Pittsburgh. The concentrated industrial structure in Pittsburgh limits the availability of capital for startups, reduces input sharing and labor pooling, and impedes entrepreneurial activities. In contrast, Rantisi (2002) reported that more than 85% of firms in New York's garment district are small- to medium-sized enterprises, which compete with each other, benefit from specialized labor and services, and monitor rival firms' performances and practices.

In a complementary research, Saxenian (1994) argued that the concept of agglomeration alone cannot explain why the two regional economies, Boston's Route 128 and northern California's Silicon Valley, diverged after the downturns in the 1980s. Both areas were centers of electronics and high-tech industries. However, when facing the changing market, Silicon Valley successfully made transition to software and other computer related industries and generated a large number of successful startups. In contrast, Route 128 failed to make the transition to smaller workstations and personal computers, which produced continuous stagnation and decline. Saxenian (1994) argued that the fundamental difference in the industrial structure between Route 128 and Silicon Valley is the key factor. Silicon Valley has a regional network-based industrial structure that promotes collective learning and horizontal communication among different firms. The Route 128 region is dominated by a small number of large corporations that do their own things, and the industrial structure is relatively rigid and hierarchical. Thus, it is difficult for firms to adjust to the changing market and for small firms to survive in Route 128.

The implication of case studies that agglomeration economies mainly arise from a large number of small firms is echoed by empirical findings in the US. Henderson (2003) showed that agglomeration economies are mainly generated through a large number of establishments rather than through the large size of establishments. Compared to medium-sized or large establishments, Rosenthal and Strange (2003) argued that small firms generate greater external effects by finding that the concentration of own-industry employment in small establishments has a larger positive impact on both the births and employment of new firms. In addition, by measuring local competition as the number of firms per worker, studies suggested that a more competitive industrial structure would promote both the employment growth (Glaeser et al., 1992) and firm birth (Rosenthal & Strange, 2003; Glaeser & Kerr, 2009).

However, very few empirical studies have addressed another important but distinct issue of how regional industrial dominance influences the performance of firms within that industry in the same region. Average firm size and the number of firm per worker can only reflect the industrial structure at an aggregated level, and neither of them can directly measure industrial dominance or industrial concentration. At an aggregated level, literature that examines the relationship between industrial concentration and industrial productivity or innovation intensity presents varying results, which differ considerably across industries, countries, and the stages of development. For example, Carree and Thurik (1999) found the influence of industrial structure concentration (employment share of large firms) on national industry output can be either positive or negative in 12 European countries, depending on industries. The results also suggested that industrial concentration may enhance production in less-developed countries, while the reverse may be the case for more-developed countries. Gopinath et al. (2004) found an inverted-U-shaped relationship between industrial concentration (four-firm concentration ratio) and productivity growth in the U.S. manufacturing industries.

With regard to industrial innovative activity, the results are even more complex. For example, early studies support Schumpeterian hypothesis that large firms and a concentrated industrial structure would promote innovative activity (Schumpeter, 1950). However, Acs and Audretsch (1988) reported a negative relationship between concentration (four-firm concentration ratio) and innovation rate at four-digit industry level. Levin et al. (1985) and Lee (2005) found that the effects of industrial concentration on innovation vary with industry conditions, such as the appropriability condition, cost of imitation, patent protection, and importance of firm's technological competence in an industry.

Feser (2002) and Drucker and Feser (2012) are the two antecedent studies directly incorporating both regional industrial dominance and agglomeration economies into plant-level production function. Measuring industrial concentration as the share of the total sales made by the four largest firms in a region, Feser (2002) found a significantly negative relationship between regional industrial dominance and plant-level productivity for the innovation-intensive measuring and controlling devices industry but no significant influence of industrial concentration for the low-tech farm and garden machinery industry. Drucker and Feser (2012) carried out the only rigorous empirical analysis, which examined both the direct effect of regional industrial dominance on plant-level productivity and its intervening effect through limiting agglomeration economies. This study used a cross-section model to jointly estimate the production function and cost-share equations for three industries in 1992, 1997, and 2002 based on the establishment-level data in the United States. Regional industrial structure concentration was measured by the percentage of the total regional industry shipment value accounted for by the five largest firms. While this study found that a concentrated regional industrial structure is directly associated with lower productivity, it did not find significant evidence that regional industrial dominance diminishes firms' productivity through limiting agglomeration economies.

3.3.4 Industrial Agglomeration in China

The level of industrial agglomeration in China has substantially increased in recent years, but it still remains lower than that in developed countries such as France, the United Kingdom, and the United States (Bai et al., 2004; Lu & Tao, 2009; Long & Zhang, 2012). Both Bai et al. (2004) and Lu and Tao (2009) attribute the low level of industrial agglomeration and specialization to market fragmentation and local protectionism. In addition, public policy also has a strong influence on industrial agglomeration in China. For example, the electronics industry exhibits an extremely high level of industrial agglomeration compared with other industries such as the textile industry, because Chinese government tries to promote the agglomeration of high-tech industries by establishing science & technology industrial parks (Yang et al., 2013).

Due to the limitation of the plant-level data, early empirical studies on the effect of industrial agglomeration on productivity in China were mainly based on the aggregated data and suggested conflicting results. For example, focusing on 23 industrial sectors in seven coastal provinces during 1985–1989, Mody and Wang (1997) found a negative impact of specialization and a positive impact of competition on the province-level industry growth. Similarly, focusing on 20 industries in 29 provinces during 1988–1995, Batisse (2002) showed that local industrial specialization has a negative impact on province-level value added growth, while diversity and competition have positive impacts. In contrast, Ke (2010) found that industrial agglomeration and the city-level labor productivity are positively, mutually, and causally related, which implies that industries tend to concentrate toward more productive areas to achieve higher productivity. In addition, Ke (2010) also reported that intercity spillover effect is a significant contributor to agglomeration, whereas productivity in neighboring cities and employment density have negative effects on productivity.

In addition, effects of agglomeration vary across cities. Based on a threshold model for 169 industries in 335 cities, Hu and Sun (2014) proposed a framework of the match between industries and cities based on the effects of agglomeration economies. The results showed insignificant impacts of both localization and urbanization economies on industrial labor productivity in large cities, positive impacts of urbanization economies and insignificant impacts of localization economies in medium-sized cities, and positive impacts of localization economies and negative impacts of urbanization economies in small cities. The results imply that large cities in China are not suitable for development of manufacturing industries, medium-sized cities provide strong spillover effects and diversity suitable for the development of high-tech industries, and small cities are the perfect locations for industrial specialization and mass production.

Using the micro-level data in China, recent studies adopt various measures of industrial agglomeration, such as the EG index (Lin et al., 2011; Yang et al., 2013; Lu & Tao, 2009), the count of plants (Li et al., 2012; Hu et al., 2015), and the count of industrial employment (Li & Lu, 2009; Li et al., 2012; Chen & Wu, 2014). In general, empirical evidence reported that industrial agglomeration is positively associated with firms' pension contribution (Chen & Wu, 2014), size (Li et al., 2012) and vertical disintegration (Li & Lu, 2009).

However, the empirical analysis on the effect of agglomeration economies on firms' productivity is ambiguous. For example, focusing on the textile industry, Lin et al. (2011) found an inverted-U-shaped relationship between agglomeration and productivity, which implies that industrial agglomeration enhances firm's productivity until agglomeration diseconomies appear after certain point. Focusing on the electronics industry, Yang et al. (2013) found that while the agglomeration of production contributes to firms' productivity, the R&D agglomeration has a negative impact on productivity. Focusing on a comprehensive range of industries, Hu et al. (2015) found that the number of firms in the same industry has a significantly negative impact on firms' productivity, which suggests that severe congestion and intense competition offset the localization economies in China. On the other hand, the results indicated that agglomeration of upstream industries and the average size of firms in the same industry have significantly positive impact on firms' productivity, implying that co-locating with large firms and upstream industries would significantly contribute to firms' productivity. Hu et al. (2015) also found that a firm's ownership structure shapes its ability to influence and to benefit from agglomeration economies. The results showed that private enterprises are the primary sources and beneficiaries of agglomeration economies, compared with state-owned enterprises or foreign-invested enterprises.

The complex empirical results in China might be attributed to two reasons. First, existing research in China fails to systematically match industries with different types and sources of agglomeration economies. Since agglomeration mechanisms differ considerably across industries, as suggested by the literature, studies confined to specific industries or focusing on all industries as a whole cannot reflect the relative importance of each mechanism for different industries. Second, there are not yet studies that consider how regional industrial dominance influences agglomeration economies and firms' productivity in China. Based on the aggregated data, Mody and Wang (1997) and Batisse (2002) measured the degree of competition as the ratio of the number of firms to total output in a region, and they found that competition has a positive impact on local growth. However, these measures are at an aggregated level and cannot directly reflect industrial dominance. In addition, neither of them examine how industrial structure influences firms' ability to benefit from agglomeration economies.

These two issues are crucial for the local/regional economic development and industrial policy, particularly in China. For example, whether an industry is subject to localization economies or urbanization economies determines if the industry would thrive in a more specialized areas or a more diverse and large urban environment. The effectiveness of a policy may differ significantly across industries and plants. In addition, if regional industrial dominance hinders firms' productivity by limiting agglomeration economies, then policy should stimulate small businesses and mitigate the negative effect of local dominant firms.

As discussed above, empirical evidence to the first issue is only limited to developed countries, and the second issue are largely unexplored in the agglomeration literature. In order to fill in the gap in the literature, this study directly measures industrial dominance in a city as industrial concentration ratio by using the plant-level data in China and examines both its direct effect and indirect effect through agglomeration economies on firms' productivity in a production function context.

3.4 Data and Methodology

3.4.1 Data

The dataset used in this study comes from China Annual Survey of Manufacturing Firms collected by the National Bureau of Statistics. This dataset contains all the state-owned enterprises (SOE) and those foreign-invested enterprises (FIE) and private enterprises (PE) with annual sales greater than 5 million RMB. The dataset provides information for each firm, including location information, industrial code, employment, output, input, materials, values of assets, etc. This dataset has been also employed by numerous studies on industrial agglomeration and firms' performance, such as Li and Lu (2009), Lin et al. (2011), Lu and Tao (2009), Li et al. (2012), Yang et al. (2013), Chen and Wu (2014), Hu et al. (2015), etc.

Because the dataset is highly unbalanced and the inclusion of a firm depends on its annual sale, this study only uses the firm-level data in 2007[16], which includes 313,047 observations. Following Hu et al. (2015), I delete the observations with invalid information for key variables, such as negative values of total industrial output, added value, employment, and age. I also drop the observations with the value of liquid assets or total fixed assets larger than total assets. After data cleaning, the sample in 2007 reduces to 306,617 observations. Based on the industry classification system, the National Bureau of Statistics defines three broader industry categories: the high-tech industry, the traditional light industry, and the traditional heavy industry (Table 1).

<Table 1 here>

3.4.2 Measuring Regional Industrial Dominance

This study calculates regional industrial structure concentration as the share of total industrial output made by the three largest firms for a three-digit industry in a city. There are various ways to measure industrial structure concentration, such as the concentration ratio, Herfindahl-Hirschman index, Theil's entropy, Rosenbluth index, Gini coefficient, etc. Empirical comparisons demonstrate that no single measure is consistently superior (Amato, 1995; Drucker, 2011). The concentration ratio measure is the most widely used and is advantageous in this study for two reasons. First, it could

[16] 2007 is the latest year that the data is available

directly measure the degree of the regional industrial dominance of the largest firms with different ownerships. Second, the concentration ratio measure is relatively insensitive to the small end of the size distribution (Drucker & Feser, 2012), which is more suitable for this study given that the dataset excludes all small firms with annual sales below 5 million RMB. In order to examine the effect of dominant firms on other firms, I exclude cities with fewer than six plants for a given industry.

In addition, I calculate three types of concentration ratio based on the ownerships of dominant firms in order to examine how the influence of regional industrial dominance varies with the ownership structures of dominant firms. Specifically, I calculate the share of total industrial output made by the largest state-owned enterprise (SOE), the largest private enterprise (PE), and the largest foreign-invested enterprise (FIE) separately for each three-digit industry in a city to measure the industrial dominance of the largest SOE, PE, and FIE in a city, respectively.

3.4.3 Measuring Agglomeration Economies

Rosenthal and Strange (2004) argue that the absolute scale measure of agglomeration reflects the direct effect of agglomeration economies whereas the relative share measure (specialization) is more about the net effect. Focusing on the absolute scale of industrial activity, there are two kinds of proxies for agglomeration economies: the count of employment and the count of firms. The count of employment for an industry measures the scale of the local industry-specific labor market, and the count of plants for an industry represents a count of local information spillover sources. Henderson (2003) argues that firms can be regarded as individual sources of knowledge spillover, so externalities are related to the count of such sources with employment size of the sources being unimportant.

In this study, I use the concentration of own-industry activities at three-digit industrial level, regarding both employment and number of firms, to measure localization economies. Following Holmes (1999), Li and Lu (2009) and Li et al. (2012), I use the concentration of related-industry activities and the concentration of other-industry activities to measure urbanization economies. A firm's related industry includes firms with different three-digit industrial codes but the same two-digit industry code, and other industry includes firms with different two-digit industry codes. Although both measures would reflect influences outside own industry, the degree of the concentration of other-industry activities presents more about the general effects of a diverse and large urban environment, and the concentration of related-industry activities can be a proxy for the industry-specific externalities that are different from but are still related to a given industry, because a firm might share similar knowledge, supplier or custom industries, or labor market with other firms in related industries (same two-digit industry code).

I use two sets of agglomeration measures. The first set uses the count of employment, focusing on labor market pooling. Localization economies are measured as the own-industry neighboring employment, which is the natural logarithm of a firm's total neighboring employment in the same city and same three-digit industry, excluding the firm's own employment. Correspondingly, I include two measures of urbanization economies: the related-industry employment and other-industry employment. The related-industry employment is the natural logarithm of a firm's total neighboring employment in the same city and same two-digit industry but different three-digit industry, and the other-industry employment is the natural logarithm of a firm's total neighboring employment in the same city but different two-digit industry.

The second set uses the count of firms, a proxy for knowledge spillover. Localization economies are measured as the count of own-industry establishments, which is the natural logarithm of the total establishments in a city for three-digit industry. Urbanization economies are measured by the number of related-industry establishments and the number of other-industry establishments.

3.4.4 Other Control Variables

The firm-specific control variables include capital intensity, welfare, training, and firm age. Capital intensity is measured by the ratio of fixed capital to employment and is expected to have a positive effect on productivity (Lee et al., 2010; Lin et al., 2011; Yang et al., 2013). Welfare controls worker benefit and is measured by ratio of expenditures on insurance and pensions to the wage, which is also expected to have a positive sign (Lin et al., 2011). Training controls the quality of human resources and is measured by the ratio of training expenditures to total wages, which is expected to have a positive sign (Yang et al., 2013). Previous studies suggest mixed results on the effect of firm age on productivity, so there is no expected sign for firm age (Lin et al., 2011; Hu et al., 2015).

3.4.5 Measuring Productivity

This study adopts total factor productivity (TFP) as the measure of productivity. TFP is the residual that obtained from the estimation of Cobb-Douglas production function. Although this study only uses the estimation of TFP for firms in 2007, in order to enhance the estimation of TFP, I use a 10-year panel data set from China Annual Survey of Manufacturing Firms (1998-2007) to estimate the log-linear production function with firm and year fixed effect:

$$lnVA_{it} = \alpha_0 + \beta_l lnL_{it} + \beta_k lnK_{it} + v_t + \mu_i + e_{it} \quad (1)$$

where $lnVA_{it}$ refers to the natural logarithm of value added for firm i in year t. lnL_{it} refers the natural logarithm of employment, and lnK_{it} refers to the natural logarithm of capital, v_t and μ_i are time and firm fixed effect. e_{it} is the overall error term.

Thus, the natural logarithm of a firm's TFP can be obtained from the estimation of the combined residual: $\mu_i + e_{it}$. Table 2 provides definition and descriptive statistics of key variables.

<Table 2 here>

3.4.6 Empirical Specification

I first estimate the following cross-sectional model for each firm i in 2007 to examine the effect of regional industrial dominance and agglomeration economies, as well as their interaction effect, on firm's TFP:

$$lnTFP_i = \alpha_0 + \beta_1 C_i + \sum_j \beta_{2j} A_{ij} + \sum_j \beta_{3j}(C_i A_{ij}) + \beta_4(Size_i C_i) + \sum_j \beta_{5j}(Size_i A_{ij})$$

$$+\beta_6 C_i^2 + \sum_j \beta_{7j} A_{ij}^2 + \gamma X_i + \mu_k + \varepsilon_i \quad (2)$$

where C_i refers to the 3-firm concentration ratio for firm i's industry in a city. A_{ij} refers to agglomeration economies for firm i. j represents different types of agglomeration economies: the concentration of own-industry activities, related-industry activities or other-industry activities.

I use both sets of agglomeration measures separately following Eq. (2). For firm i, A_{ij} could be either the employment of the own-industry/related-industry/other-industry or the number of firms of own-industry/related-industry/other-industry, standing for labor market pooling effect or knowledge spillover effect, respectively. The interaction term $C_i A_{ij}$ allows me to examine how the productivity effect of agglomeration economies changes with the level of regional industrial structure concentration. The interaction term $Size_i C_i$ and $Size_i A_{ij}$ allow me to examine how the effects of regional industrial dominance and the effects of agglomeration economies on productivity vary with firm size. X_i is a vector of firm-specific control variables. μ_k is the province fixed effect. I also incorporate quadratic terms of concentration ratio and agglomeration economies to control for the nonlinear effects.

In an extended model, I decompose the regional industrial dominance into three parts based on the ownership of a dominant firm and re-estimate the cross-sectional model for each firm i in 2007 following Eq. (3):

$$lnTFP_i = \alpha_0 + \sum_w \beta_{1w} C_{iw} + \sum_j \beta_{2j} A_{ij} + \sum_w \sum_j \beta_{3wj}(C_{iw} A_{ij}) + \sum_w \beta_{4w}(Size_i C_{iw})$$

$$+ \sum_j \beta_{5j}(Size_i A_{ij}) + \beta_6 C_i^2 + \sum_j \beta_{7j} A_{ij}^2 + \gamma X_i + \mu_k + \varepsilon_i \quad (3)$$

where C_{iw}refers to three types of concentration ratio, the industrial concentration ratio of the largest SOE, PE or FIE in a city. Differences in the coefficients of C_{iw} can reveal how the effect of a dominant firm on other firms' productivity varies with the ownership of the dominant firm. The interaction term $C_{iw} A_{ij}$ examines how the ownership structure of a dominant firm shapes its ability to limit agglomeration economies.

3.5 Empirical Results and Discussion

I estimate Eq. (2) using both the employment measure and the count of firm measure of agglomeration economies for the high-tech industry, the traditional light industry, and the traditional heavy industry. The results are reported in Table 3. The coefficients of all the control variables are significant and have the expected signs. The plant-level productivity is positively associated with capital intensity, welfare and training but negatively associated with firm age.

<Table 3 here>

3.5.1 Agglomeration Economies

Different industry categories benefit from different mechanisms of agglomeration economies. In general, the results indicate that knowledge spillover effects and a large and diverse urban environment (the concentration of other-industry activities) are more important for the high-tech industry, whereas the traditional light industry mainly benefits from a more specialized urban environment, particularly the own-industry labor market pooling and the concentration of related-industry activities. The results lend support for the product life-cycle location theory. Surprisingly, I find that the traditional heavy industry mainly benefits from urbanization economies or the concentration of other-industry activities, which is contrary to the conventional wisdom but supported by Feser (2001) and Ehrl (2013). Both productivity and agglomeration economies are in the natural logarithmic form, so the coefficients show elasticity at sample means.

As for the high-tech industry, in terms of localization economies (A_1), the spillover effect is more important than labor market pooling. The coefficient of localization economies is positive but not significant when measured by the count of the own-industry employment (A_1, *Employment*), but it's highly significant and positive when localization economies are measured by the count of own-industry firms (A_1, *#firm)*. The estimation indicates that a 10% increase in the number of own-industry firms in a city would lead to around 1.94% increase in the productivity of high-tech firms.

With regard to urbanization economies (A_2, A_3), high-tech firms would benefit from a more diverse and large urban environment in terms of both employment and number of firms. Urbanization economies enhance productivity of high-tech firms mainly through the concentration of other-industry activities (A_3). The concentration of the related industry (same two-digit industry) has significant and negative effect on productivity when using both employment and firm measure, whereas the concentration of other-industry (different two-digit) employment and firms have significantly positive effect on productivity of firms in the high-tech industry. A 10% increase in the employment and the number of other-industry firms in a city would lead to around 17.9% and 5% increase in the productivity of high-tech firms. This implies that a high-tech firm would benefit from co-locating with other manufacturing establishments that are very different from it.

In the traditional light industry, regarding localization economies, labor market pooling is more important than spillover effect. A 10% increase in the own-industry employment in a city would lead to around 1% increase in the productivity of firms in the traditional light industry. The number of own-industry firms in a city only exhibits positive but insignificant effect on productivity. In terms of urbanization economies, traditional light industries only benefit from the concentration of related industries (same two-digit industry). A 10% increase in the employment and the number of related-industry firms in a city would lead to around 1.9% and 1.7% increase in the productivity of firms in the traditional light industry. Contrary to high-tech industries, a larger and more diverse urban environment would negatively influence the productivity of traditional light industries, as the concentration of other-industry (different two-digit) activities has significantly negative effect on the productivity of firms in the traditional light industry.

In the traditional heavy industry, firms only benefit from urbanization economies that measured by the concentration of other-industry activities. The localization economies have significantly negative effect on productivity. The concentration of related-industry activities would also significantly hinder productivity when agglomeration is measured by the related-industry employment. However, firms in the traditional heavy industry would benefit from a large and diverse market with high concentration of employment and firms in other two-digit industries. A 10% increase in the employment and the number of other-industry firms in a city would lead to around 4.8% and 3.1% increase in the productivity of firms in the traditional heavy industry, respectively.

The findings on the traditional heavy industry are in line with some previous studies. Ehrl (2013) argues that firms in heavy industries may still compete for innovation and technological advances, although they have relatively low R&D investments. Feser (2001) has reached similar results for the US farm and garden machinery industry. He argues that industries producing less knowledge-intensive goods typically require workers with less specialized skills and these industries may benefit more from the general advantage of a large and diverse urban environment. Furthermore, Henderson (2003) suggests that the overall local scale can capture the effects of unmeasured business service inputs. Thus, he found evidence of urbanization-scale economies for machinery corporate plants but not for high-tech firms, because machinery plants outsource more materials than high-tech plants.

The discussion above only focuses on the direct effect of agglomeration economies on productivity. However, agglomeration economies also influence firms' productivity nonlinearly since the quadratic terms are all significant.

In addition, the results also show that the effects of agglomeration economies vary with firm size. More specifically, large firms benefit relatively more from localization economies (the concentration of own-industry activities), whereas urbanization economies, when measured by the concentration of other-industry activities, are more important for small firms. The coefficients of the interaction terms between firm size and localization economies measured by both employment and number of firm *(size*own-industry)* are all significantly positive, which implies that plants with larger size experience stronger positive effect of a given level of localization economies. The coefficients of the interaction terms between firm size and the concentration of other-industry activities (*size*other-industry*) are all significantly negative, so that smaller plants would do better in a more diversified and larger urban environment. These conclusions are in consonance with the findings of Lee et al. (2010).

3.5.2 Regional Industrial Dominance

Since the three-firm concentration ratio is in level term while productivity is in the natural logarithmic form, the coefficients of the concentration ratio show the semi-elasticity evaluated at sample mean of independent variable.

The results in table 3 show significantly direct negative influence of regional industrial dominance on firms' productivity. A 1% higher three-firm concentration ratio *(C)* is associated with 3.7% or 2.4% lower productivity of firms in the high-tech industry, 4.5% or 3% lower productivity in the traditional light industry, and 1.7% or 2.4% lower productivity in the traditional heavy industry. These imply that firms are less productive in cities where their own industry is dominated by a few large firms, holding other factors equal. The coefficients of quadratic terms of concentration ratio are significant and positive in models when agglomeration economies are measured by employment, which implies that the negative effect of industrial structure concentration decreases as the level of concentration increases.

Furthermore, the effect of regional industrial dominance on productivity also varies with firm size. The coefficients of the interaction terms between firm size and concentration ratio (*size*concentration*) are all significant and positive in all models, which implies that smaller plants experience greater negative impact of regional industrial dominance. In other words, a concentrated industrial structure in a city might enhance the productivity of the largest plants but is more of a hindrance to the productivity of small plants. Drucker and Feser (2012) drew similar conclusions for the rubber and plastics industry in the US.

The primary focus of this study is how regional industrial dominance influences the productivity effects of agglomeration economies. The results show that the dominance of a few large firms in an industry may hinder other firms' productivity by preventing them from taking advantage of localization economies in a city. The coefficients of the interaction terms between *concentration* and *own-industry employment/firms* are all significantly negative for all industry categories, leading to the conclusion that the positive productivity effect of a given level of localization economies would be smaller in cities with higher degree of industrial structure concentration.

As for both the high-tech industry and traditional heavy industry, regional industrial dominance limits firms' ability to benefit from both own-industry labor market pooling and knowledge spillover effect, since the coefficients of the interaction terms between dominance and both employment and firm measure of localization economies are significantly negative. Regarding the traditional light industry, higher level of industrial dominance mainly lowers productivity through limiting own-industry spillover effect, since only the interaction term between *concentration* and *own-industry firms* has significantly negative impact in traditional light industry. Drucker and Feser (2012) found similar patterns for the rubber and plastics industry and measuring and controlling devices industry in 2002 in the US.

On the other hand, the negative interaction between dominance and localization economies also suggests that in cities lacking localization economies, firms may benefit from the dominant large firms. Drucker and Feser (2012) argue that locally dominant firms may create some alternative positive spillover effects in areas lacking agglomeration economies.

The results on the interaction terms between dominance and various measures of urbanization economies suggest that the negative productivity effect of regional industrial dominance might be mitigated in a more diverse and larger urban environment. Firms may turn to the externalities derived from other industries when their own industry is dominated by a few large firms that limit localization economies.

In the high-tech industry and traditional heavy industry, both the interaction terms between *concentration* and *related-industry* and between *concentration* and *other-industry* have positive coefficients, which implies that the negative impact of a given level of regional industrial dominance on productivity is smaller in the presence of higher level of urbanization economies. The concentration of both related-industry activities and other-industry activities would create alternative advantages for firms in high-tech and traditional heavy industries in cities where their own industry is dominated by a few large firms.

As for the traditional light industry, the negative interaction terms between *concentration* and *related-industry* indicate that regional industrial dominance would limit firms' access to both the labor market pooling and spillover effect from the concentration of related-industry activities, while the positive interaction terms between *concentration* and *other-industry* suggest that the negative effects of dominance would be mitigated by the concentration of other-industry activities.

3.5.3 Regional Industrial Dominance by Firm Ownership

In order to understand how the effects of regional industrial dominance vary with the ownerships of dominant firms, I estimate Eq. (3) and the results are reported in Table 4.

<Table 4 here>

There are three main findings. First, regarding the direct effect of regional industrial dominance, the values of the share of the total own-industry output in a city made by the largest SOE (C_1), the largest PE (C_2) and the largest FIE (C_3) are all have negative influences on firm-level productivity, except that a dominant SOE has an insignificant impact on productivity of firms in the traditional light industry.

In the high-tech industry, dominant foreign-invested enterprises have the least negative effect on firm-level productivity. A 1% higher concentration ratio of the largest SOE, the largest PE and the largest FIE in a city is associated with 3.7% or 3%, 3.9% or 3.7%, and 2.1% or 1.4% lower productivity of firms in the high-tech industry, respectively.

As for the traditional light industry, dominant state-owned enterprises may not influence firm-level productivity. The concentration ratio of the largest SOE in a city does not have a significant impact on productivity of firms in the traditional light industry, whereas dominant PE and FIE have significantly negative influences. A 1% higher concentration ratio of the largest PE and the largest FIE is associated with 3.9%

or 2.8% and 3.8% or 3.6% lower productivity, respectively, for the traditional light industry.

For the traditional heavy industry, both dominant SOE and PE have significantly negative influences on productivity, with dominant PE having the largest negative effect. A 1% higher concentration ratio of the largest SOE and the largest PE is associated with 1.2%, and 2.3% or 2.6% lower productivity, respectively. The concentration ratio of the largest FIE only has a significantly negative impact in the model using firm measure of agglomeration economies: a 1% higher concentration ratio of the largest FIE is associated with about 1.37% lower productivity of firms in the traditional heavy industry.

In addition, the interaction terms between firm size and concentration ratio of the largest SOE, PE and FIE are all positive, which confirms the previous finding that smaller plants experience greater negative effects of regional industrial dominance and that larger plants may benefit from a concentrated industrial structure.

Second, the effects of agglomeration economies on productivity vary with the level of regional industrial dominance measured by concentration ratios of the largest SOE, PE and FIE. With regard to the high tech industry and traditional heavy industry, dominant SOE, PE and FIE would hinder local plants from accessing both labor market pooling and spillover effect of localization economies, since the coefficients of the interaction terms between *concentration SOE/PE/FIE* and *own-industry employment/firms* are all significant and negative. Regardless of the ownership structure of dominant firms, firm-level productivity would be lower than expected at the same level of localization economies in a city when the own industry is dominated by a few large firms.

However, the traditional light industry is a different story. For the traditional light industry, both the dominant SOE and FIE would limit local plants' ability to benefit from localization economies, but it's not the case for the largest PE. The interaction terms between the *concentration SOE/FIE* and *own-industry employment/firms* have significantly negative impact on productivity. But the coefficients of the interaction terms between the *concentration PE* and *own-industry employment/firms* are all positive, which implies that while a dominant private firm in the traditional light industry has direct negative influence on the productivity of other firms, the localization economies are not the mediating mechanism for this negative influence. In fact, the results show that a dominant private firm would enhance the positive effect of localization economies in the traditional light industry, especially the effects of own-industry labor market pooling, since the coefficient of the interaction term between *Concentration PE* and *own-industry employment* is significant and positive.

Third, with regard to the interaction terms between dominance and urbanization economies, the results substantiate the finding that a diverse and large urban environment would mitigate the negative impact of regional industrial dominance. As for the high-tech industry, the negative productivity effects of the dominant FIE would be mitigated by the concentration of related-industry activity and the negative impact of the dominant SOE and PE can be reduced by the concentration of other-industry activity. In the traditional light industry, both the concentration of other-industry employment and firms would weaken the negative effects of dominant PE and FIE. In the traditional heavy industry, the concentration of related-industry activity would mitigate the negative productivity effects of regional industrial dominance regardless of the ownerships of dominant firms, while the concentration of other-industry activity can further alleviate the negative effects of dominant private firms.

3.6 Conclusion and Policy Implication

Industrial agglomeration is an important source for productivity growth and innovation, and making the best of industrial agglomeration is crucial for the on-going industrial transformation and upgrading in China. Using 2007 firm-level data in Chinese manufacturing industries, this study estimates firm-level production function by incorporating various measures of agglomeration economies and regional industrial dominance. The primary finding directly contributes to the literature of agglomeration economies and industrial structure by finding regional industrial dominance as an influential factor that diminishes productivity by hindering firms from taking advantage of localization economies. Previous studies on agglomeration in China may suffer from its omission.

More specifically, the empirical analysis first demonstrates that firms are less productive in cities where their own industry is dominated by a few large firms, particularly for small firms. Next, the significantly negative interaction between dominance and measures of localization economies implies that regional industrial dominance would limit the positive productivity effect of localization economies. The results lend support for Chinitz (1961) and Saxenian (1994) who argue that industrial agglomeration would generate fewer externalities in regions where an industry is dominated by a few large firms. Furthermore, the analysis on the interaction terms between dominance and various measures of urbanization economies suggest that the negative productivity effect of regional industrial dominance might be alleviated in a more diverse and larger urban environment.

Further investigation on how the difference in the ownership of dominant firms influences the productivity effects of regional industrial dominance substantiates the primary finding. The results show that the concentration ratios of the largest SOE, the largest PE and the largest FIE in a city are all associated with lower productivity of firms, except that a dominant SOE in a city has an insignificant productivity effect in the traditional light industry. Despite dominant private firms in the traditional light industry, regional industrial dominance seems to result in fewer positive externalities of localization economies for all other cases.

This study also finds that different industry categories benefit from different mechanisms of agglomeration economies, which may partly explain the mixed results in the literature on agglomeration in China. In general, empirical evidence suggests that knowledge spillover effects and a large and diverse urban environment are more important for the high-tech industry, whereas the traditional light industry mainly benefits from a more specialized urban environment. The results lend support for the product life-cycle location theory. Surprisingly, it is found that firms in the traditional heavy industry mainly benefit from a large overall scale of other industries with different two-digit industry codes in a city. I interpret this as evidence of the general advantage of a large urban environment (Feser, 2001) and the effects of unmeasured business service inputs (Henderson, 2003).

There are several important policy implications derived from the empirical analysis. First, due to the negative impact of regional industrial dominance on both firms' productivity and productivity effects of agglomeration economies, policies that promote industrial agglomeration should also focus on creating a competitive regional industrial structure. While attracting large firms could boost short-term regional/local economic and employment growth, it is the presence of a large number of small firms that generates greater external economies, creates new jobs, and stimulates radical innovation and entrepreneurship, which would drive the rise of new industries and long-term competitiveness. Therefore, policies should stimulate small firms, which are particularly vulnerable to the negative influence of regional industrial dominance. Such policies may include reducing market entry barriers, fostering entrepreneurship, facilitating access to capital and investment for small firms, promoting collaboration, and protecting intellectual property rights.

Second, given the positive productivity effects of agglomeration economies in general, government should continue promoting industrial agglomeration by reducing local protectionism, removing interregional trade barriers, limiting finance resources for inefficient local firms, etc. Meanwhile, governments should note that because the mechanisms of agglomeration economies vary with industries and plants, industries and firms may require different economic environments to thrive. For example, smaller plants and innovative industries may do better in a more diverse and larger urban environment, while large mature plants and traditional light industries may take more advantage from a more specialized area.

Table 1. Industry classification

	Industries (two-digit industrial code)
High-tech industries	Pharmaceutical industry(27) Special-purpose equipment manufacturing (36) Manufacturing of railways, ships, aircrafts, space crafts and other transportation equipment (37) Electric machinery and equipment manufacturing(39) Manufacturing of computers, communications and other electronic equipment (40) Instrument, meter and office manufacturing (41)
Traditional light industries	Agricultural and sideline food processing industry (13) Food manufacturing(14) Alcohol, beverage and refined tea manufacturing(15) Tobacco manufacturing(16) Textile industry(17) Textile garment and apparel industry(18) Leathers, furs, feathers and related products and footwear industry(19) Wood processing and wood, bamboo, rattan, Palm fiber, and straw product industry (20) Furniture manufacturing (21) Papermaking and paper product industry (22) Manufacturing of stationery, industrial arts, sports and entertainment supplies(24)
Traditional heavy industries	Industries of petroleum processing, coking, and nuclear fuel processing(25) Chemical fiber manufacturing(26) Chemical fiber manufacturing(28) Industry of rubber products(29) Industry of plastic products(30) Industry of non-metallic mineral products(31) Industry of non-ferrous metal(32) Industry of ferrous metal smelting and rolling processing(33) Metal product industry(34) General equipment manufacturing(35)

Table 2. Definition and descriptive statistics of variables

Variables	Definition	Mean	Std. Dev.
$lnTFP$	The residual obtained from the estimation of production function	0.035	1.038
3-firm concentration ratio **(C)**	The share of total industrial output made by the three largest firms for a 3-digit industry in a city (Feser, 2002; Drucker & Feser, 2012)	0.482	0.279
Concentration SOE (C_1)	The share of total industrial output made by the largest state-owned firm for a 3-digit industry in a city	0.051	0.124
Concentration PE (C_2)	The share of total industrial output made by the largest private firm for a 3-digit industry in a city	0.202	0.217
Concentration FIE (C_3)	The share of total industrial output made by the largest foreign-invested firm for a 3-digit industry in a city	0.115	0.161
Own-industry employment (A_1)	Firm's total neighboring employment in the same city and same 3-digit industry (in natural log) (Henderson, 1997; Henderson et al., 2001; Rosenthal, 2003; Lall et al., 2004; Lee et al., 2010; Li et al., 2012; Chen & Wu, 2014, etc.)	8.811	1.805
Related-industry employment (A_2)	Firm's total neighboring employment in the same city and same 2-digit industry but different 3-digit industry (in natural log) (Holmes, 1999; Li & Lu, 2009; Li et al., 2012)	9.406	1.833
Other-industry employment (A_3)	Firm's total neighboring employment in the same city but different 2-digit industry (in natural log) (Holmes, 1999; Rosenthal et al., 2003; Henderson, 2003; Li & Lu, 2009; Li et al., 2012)	12.961	1.232
Own-industry establishments (A_1)	Total establishments in a city for 3-digit industry (in natural log) (Henderson, 2003; Lee et al., 2010; Hu et al., 2015)	3.680	1.553
Related-industry establishments (A_2)	Total establishments in the same city and same 2-digit industry but different 3-digit industry (in natural log) (Li et al., 2012)	4.234	1.685
Other-industry establishments (A_3)	Total establishments in the same city but different 2-digit industry (in natural log) (Li et al., 2012)	7.624	1.23
Capital intensity	Ratio of fixed capital to employment	103.356	304.922
Welfare	Ratio of expenditures on insurance and pensions to the wage	0.112	0.438
Training	Ratio of training expenditures to total wages	0.009	0.060
Age	Firm age	8.016	9.15
Size	Firm's employment (in natural log)	4.626	1.07

Table 3. Effects of regional industrial dominance and agglomeration economies on TFP (in natural log)

	High-tech industry		Traditional light industry		Traditional heavy industry	
	Employment	**#firm**	**Employment**	**#firm**	**Employment**	**#firm**
Concentration (*C*)	-3.745***	-2.437***	-4.519***	-3.089***	-1.681***	-2.423***
	(0.512)	(0.397)	(0.283)	(0.266)	(0.293)	(0.277)
Own-industry (log) (A_1)	0.031	0.194***	0.111***	0.038	-0.112**	-0.372***
	(0.050)	(0.060)	(0.037)	(0.047)	(0.051)	(0.061)
Related-industry (log) (A_2)	-0.534***	-0.368***	0.190***	0.174***	-0.049**	-0.012
	(0.034)	(0.033)	(0.017)	(0.014)	(0.020)	(0.017)
Other-industry(log) (A_3)	1.788***	0.504***	-0.562***	-0.284***	0.478***	0.311***
	(0.147)	(0.107)	(0.072)	(0.052)	(0.066)	(0.049)
Concentration*own-industry(log)	-0.141***	-0.272***	-0.01	-0.088**	-0.074***	-0.079*
	(0.024)	(0.040)	(0.017)	(0.034)	(0.021)	(0.042)
Concentration*related-industry(log)	0.173***	0.174***	-0.142***	-0.235***	0.065***	0.115***
	(0.022)	(0.028)	(0.010)	(0.011)	(0.012)	(0.013)
Concentration*other-industry(log)	0.160***	0.156***	0.323***	0.395***	0.018	0.032*
	(0.038)	(0.041)	(0.018)	(0.019)	(0.017)	(0.018)
Size(log)*concentration	0.214***	0.332***	0.219***	0.257***	0.161***	0.268***
	(0.019)	(0.020)	(0.017)	(0.019)	(0.015)	(0.016)
Size(log)*own-industry(log)	0.04***	0.066***	0.014***	0.021***	0.039***	0.073***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)
Size(log)*relate-industry(log)	0.02***	0.038***	0.004**	0.006***	-0.004	-0.001
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Size(log)*other-industry(log)	-0.032***	-0.043***	-0.011***	-0.015***	-0.018***	-0.032***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Concentration^2	0.37***	0.109	0.389***	-0.083	0.271***	0.167
	(0.132)	(0.158)	(0.090)	(0.126)	(0.089)	(0.125)
Own-industry^2	-0.009***	-0.05***	-0.013***	-0.016***	-0.006**	-0.004
	(0.002)	(0.005)	(0.002)	(0.004)	(0.003)	(0.005)
Relate-industry^2	0.02***	0.01***	-0.011***	-0.019***	0.005***	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Other-industry^2	-0.064***	-0.017***	0.021***	0.017***	-0.015***	-0.01***
	(0.005)	(0.006)	(0.003)	(0.003)	(0.002)	(0.003)
Capital labor intensity	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Welfare	0.182***	0.178***	0.095***	0.097***	0.191***	0.192***
	(0.066)	(0.064)	(0.024)	(0.026)	(0.057)	(0.057)
Training	0.765***	0.761***	0.740***	0.747***	0.4***	0.394***
	(0.152)	(0.152)	(0.081)	(0.082)	(0.094)	(0.095)
Age	-0.008***	-0.008***	-0.001**	-0.001**	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Constant	-8.691***	-1.379***	2.642***	0.588**	-2.487***	-0.412*
	(0.988)	(0.436)	(0.488)	(0.232)	(0.484)	(0.226)
Observations	39,337	39,337	86,096	86,096	86,400	86,400
R-squared	0.18	0.177	0.099	0.096	0.107	0.11

Note: Robust standard errors are in parentheses. All estimations include province fixed effect.
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Estimates of the effects of agglomeration economies and the dominance of the largest state-owned enterprises (SOE), private enterprises (PE) and foreign invested enterprises (FIE)

	High-tech industry		Traditional light industry		Traditional heavy industry	
	Employment	**#firm**	**Employment**	**#firm**	**Employment**	**#firm**
Concentration SOE (C_1)	-3.726***	-2.983***	0.201	-0.203	-1.210**	-1.245***
	(0.842)	(0.528)	(0.637)	(0.445)	(0.537)	(0.319)
Concentration PE (C_2)	-3.906***	-3.671***	-3.861***	-2.797***	-2.326***	-2.614***
	(0.527)	(0.364)	(0.408)	(0.288)	(0.376)	(0.267)
Concentration FIE (C_3)	-2.106***	-1.386***	-3.825***	-3.601***	-0.376	-1.367***
	(0.604)	(0.390)	(0.367)	(0.271)	(0.365)	(0.262)
Own-industry (log) (A_1)	0.123***	0.180***	0.276***	0.133***	-0.055	-0.195***
	(0.047)	(0.048)	(0.030)	(0.032)	(0.044)	(0.043)
Related-industry (log) (A_2)	-0.314***	-0.143***	0.173***	0.141***	-0.058***	-0.003
	(0.034)	(0.033)	(0.017)	(0.014)	(0.020)	(0.017)
Other-industry(log) (A_3)	1.595***	0.370***	-0.318***	-0.102*	0.440***	0.254***
	(0.148)	(0.105)	(0.073)	(0.053)	(0.070)	(0.049)
Concentration SOE *own(log)	-0.175***	-0.255***	-0.099**	-0.240***	-0.031	-0.154***
	(0.042)	(0.053)	(0.043)	(0.057)	(0.034)	(0.051)
Concentration PE *own(log)	-0.195***	-0.287***	0.049***	0.022	-0.110***	-0.123***
	(0.027)	(0.038)	(0.018)	(0.027)	(0.025)	(0.041)
Concentration FIE *own(log)	-0.140***	-0.168***	-0.253***	-0.257***	-0.166***	-0.236***
	(0.026)	(0.036)	(0.027)	(0.038)	(0.026)	(0.037)
Concentration SOE *relate(log)	-0.167***	-0.245***	-0.03	-0.095***	0.075**	0.117***
	(0.046)	(0.056)	(0.030)	(0.035)	(0.031)	(0.034)
Concentration PE *relate(log)	-0.053*	-0.170***	-0.215***	-0.293***	0.076***	0.147***
	(0.029)	(0.039)	(0.018)	(0.020)	(0.018)	(0.020)
Concentration FIE *relate(log)	0.244***	0.333***	-0.113***	-0.234***	0.086***	0.094***
	(0.030)	(0.036)	(0.019)	(0.023)	(0.021)	(0.023)
Concentration SOE *other(log)	0.461***	0.491***	0.007	0.084	-0.013	-0.007
	(0.077)	(0.081)	(0.065)	(0.066)	(0.039)	(0.042)
Concentration PE *other(log)	0.381***	0.494***	0.305***	0.342***	0.076***	0.057**
	(0.045)	(0.054)	(0.032)	(0.033)	(0.027)	(0.028)
Concentration FIE *other(log)	0.02	-0.077	0.375***	0.460***	-0.028	0.027
	(0.053)	(0.053)	(0.032)	(0.032)	(0.033)	(0.034)

Note: Robust standard errors are in parentheses. All estimations include province fixed effect.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4 continues

	High-tech industry		Traditional light industry		Traditional heavy industry	
	Employment	#firm	Employment	#firm	Employment	#firm
Size(log) * concentration SOE	0.051	0.108***	0.158***	0.168***	0.167***	0.262***
	(0.035)	(0.036)	(0.046)	(0.046)	(0.032)	(0.032)
Size(log) * concentration PE	0.195***	0.250***	0.191***	0.231***	0.208***	0.317***
	(0.027)	(0.028)	(0.025)	(0.025)	(0.022)	(0.023)
Size(log) * concentration FIE	0.205***	0.294***	0.342***	0.357***	0.174***	0.246***
	(0.029)	(0.029)	(0.030)	(0.032)	(0.029)	(0.030)
Size(log)*own-industry(log)	0.037***	0.047***	0.012***	0.011***	0.038***	0.065***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)
Size(log)*relate-industry(log)	0.017***	0.027***	0.003	0.006***	-0.003	-0.002
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Size(log)*other-industry(log)	-0.025***	-0.018***	-0.008***	-0.007**	-0.017***	-0.025***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Concentration SOE^2	1.160***	0.870***	-0.000	-0.234	-0.348**	-0.556***
	(0.179)	(0.182)	(0.216)	(0.212)	(0.146)	(0.143)
Concentration PE^2	0.382**	0.379***	0.424***	0.057	0.360***	0.203
	(0.150)	(0.146)	(0.131)	(0.133)	(0.122)	(0.135)
Concentration FIE^2	-0.002	-0.008	0.297**	-0.083	0.178	-0.063
	(0.140)	(0.149)	(0.131)	(0.141)	(0.131)	(0.135)
Own-industry^2	-0.014***	-0.048***	-0.020***	-0.022***	-0.008***	-0.014***
	(0.002)	(0.004)	(0.001)	(0.003)	(0.002)	(0.004)
Relate-industry^2	0.012***	-0.001	-0.011***	-0.018***	0.005***	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Other-industry^2	-0.059***	-0.018***	0.013***	0.006*	-0.013***	-0.007**
	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
Capital labor intensity	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Welfare	0.185***	0.184***	0.094***	0.095***	0.192***	0.192***
	(0.068)	(0.067)	(0.025)	(0.026)	(0.057)	(0.057)
Training	0.771***	0.769***	0.749***	0.753***	0.397***	0.389***
	(0.152)	(0.151)	(0.082)	(0.082)	(0.094)	(0.094)
Age	-0.007***	-0.008***	-0.001**	-0.001**	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Constant	-9.072***	-1.200***	-0.045	-0.439**	-2.683***	-0.873***
	(0.947)	(0.389)	(0.478)	(0.209)	(0.482)	(0.190)
Observations	39,337	39,337	86,096	86,096	86,400	86,400
R-squared	0.182	0.18	0.098	0.094	0.105	0.108

Note: Robust standard errors are in parentheses. All estimations include province fixed effect.
*** p<0.01, ** p<0.05, * p<0.1

Chapter 4: Consumption and City Size: Evidence from China

4.1 Abstract

Recent work on consumption-side agglomeration economies argues that large cities can enhance household consumption. Using data from the 2011 China Household Finance Survey (CHFS), this study reveals a positive relationship between city size and various categories of household consumption expenditures. The results suggest that households spend more on dining out, daily necessities, housekeeping services, entertainment, education, healthcare, travel, and clothing in larger cities, after controlling for household size and income level. The results are further substantiated by the Tobit model ML estimation and IV 2SLS estimation. The analysis of region/location fixed effect indicates that households ceteris paribus have higher consumption expenditures in the more developed eastern region, central cities and large towns than the western/central region, outskirts and small town/rural areas. The findings point to the crucial role of a market-driven urbanization process in facilitating the transition to a consumption-driven growth in the context of China.

4.2 Introduction

Using data from the 2011 China Household Finance Survey (CHFS), this paper contributes to a small but growing body of research on the role of large cities in enhancing consumption. Very few studies have directly examined the relationship between city size and consumption patterns due to the scarcity of consumption data.

The only two available empirical tests found a positive relationship between city size and the frequency of visiting bars, concerts, restaurants, theatres, etc. (Glaeser & Gottlieb, 2006; Borck, 2007). To fill the gap in the literature, this study constitutes the first attempt to find direct quantitative evidence of whether urban scale has a positive effect on household consumption expenditures on various kinds of goods or services, other things being equal.

While studies on agglomeration traditionally have focused on the productivity-enhancing effect of cities, an emerging literature has emphasized the consumption-side benefit of cities and argues that cities also serve as centers of consumption, or so-called the "consumer city" (Glaeser et al., 2001). Large cities can enhance consumption. The reasons are several. First, large cities facilitate face-to-face contact; hence, consumers in larger cities may have higher demand for goods and services that can facilitate social contact (Banta, 1989; Glaeser & Gottlieb, 2006; Cosman, 2014). In addition, influences of peer pressure and social comparison may be more significant in larger cities, which would affect consumer's desire to buy what others buy, and thus large-city consumers may be more likely to purchase luxury goods (Elliott & Leonard, 2004; Karlsson et al., 2005; Handbury & Weinstein, 2015).

Second, some goods and services that have substantial scale economies can only be available in large urban markets with enough consumers, such as museums, professional sport teams, rare cuisines, etc. (Glaeser et al., 2001; Hsu, 2012; Schiff, 2014). Third, larger cities provide a greater variety of goods, which would allow consumers to find what fits their tastes more successfully due to "preference externalities" (Waldfogel, 1999; Waldfogel et al., 2004; Couture, 2015). Fourth, larger cities may also provide more high-quality products (George & Waldfogel, 2000; Berry & Waldfogel, 2010). Finally, consumers may also benefit from lower price of identical goods in larger cities (Handbury & Weinstein, 2014).

Although evidence for agglomeration economies in consumption in large cities exists, most of it is indirect. The idea of consumption-side agglomeration economies plays a central role in recent work on urban wage premium. The key idea is that people are willing to pay to enjoy consumption possibilities in large cities. Agglomeration economies imply that productivity and nominal wages increase with city size due to input sharing, labor market pooling and knowledge spillover, while congestion effects increase housing costs, crime, pollution in large cities (Rosenthal & Strange, 2004). In the equilibrium, agglomeration economies in large cities should offset the high cost of living and other diseconomies.

However, empirical analysis in the United States and Japan indicated that rent increases with city size faster than nominal wage, which is interpreted as evidence that people may give up real wage to enjoy consumption amenities in large cities (Tabuchi & Yoshida, 2000; Glaeser et al., 2001; Glaeser & Gottlieb, 2006). In addition, recent studies on the consumption-side explanation for urban wage premium have attributed the high wage in large cities to the selection of high-skill workers sorting into large cities driven by the taste for consumption amenities, which points to the consumption benefits of large cities (Adamson et al., 2004; Lee, 2010).

Furthermore, literature on urban growth has also emphasized the important role that consumption opportunities play in enhancing attractiveness of a city. Empirical evidence suggests a positive correlation between consumption amenities and population/employment growth (Glaeser et al., 2001; Shapiro, 2006; Buch et al., 2014)

The evidence that rents grow faster than nominal wages found in Japan and the United States also applies to large cities in China. Except for tourism cities, most cities in China that have the highest housing-price-to-income ratio are the largest and most developed cities, such as Beijing, Shanghai, Shenzhen, Guangzhou (Lu, 2015). Meanwhile, large cities in China still have experienced a divergent growth pattern in the past two decades (Li & Ding, 2014). For example, as both a political and economic center in China, the housing-price-to-income ratio in Beijing has doubled between 2000 and 2010, and all income groups have faced an increase in housing-price-to-income ratio (Yao, 2011). This implies that the housing price has been rising faster than wages in Beijing. However, the urban population in Beijing has still increased by 1.5 times during this period (NSB, 2010). This suggests that the increase in productivity and nominal wage due to agglomeration economies alone cannot explain the attractiveness and fast growth of Beijing city.

Besides the high productivity in large cities in China, residents in large cities also benefit from consumption possibilities. For instance, about 85% mainstream consumers are disproportionately concentrated in the 100 wealthiest cities in China, which may point to the consumption benefits of large cities in China (Atsmon & Magni, 2012). By examining the relationship between household consumption expenditures and city size, this study finds that households in larger cities ceteris paribus spend more on dining out, daily necessities, housekeeping services, entertainment, education, travel, healthcare and clothing. The main results are further substantiated by the Tobit model ML estimation and IV 2SLS estimation, which have addressed some potential econometric issues.

The results lend direct support to the role of large cities in enhancing consumption, consistent with the "consumer city" literature. These results also have profound policy implications in the context of China. Among major economies in the world, China has the lowest household consumption as a share of GDP. Thus, China's economic structure is currently in transition from manufacturing to services and from investment and exports to consumption. This transition can take advantage of a more efficient urbanization process, in particular the important role of large cities in enhancing both productivity and consumption.

This paper is organized as follows. The next section provides a brief overview of the related literature. Section 4.4 describes data and methods used in this study. Section 4.5 discusses results and section 4.6 gives main conclusions and final remarks.

4.3 Literature

4.3.1 Agglomeration for Consumption

Recent studies on agglomeration has shifted their attention to the consumption-side advantage of cities. In the paper "consumer city", Glaeser et al. (2001) argue that cities (agglomeration) can not only enhance productivity but also facilitate consumption. On the production side, agglomeration would enhance productivity and raise nominal wages through input sharing, labor market pooling and knowledge spillover (Rosenthal & Strange, 2004). However, higher wages would raise the demand for land, leading to higher urban rent (Glaeser et al., 2001).

On the consumption side, urban scale also has significant influence on quality of life through a diverse group of scale-related amenities and disamenities (Clark et al., 1988). For example, residents in bigger cities would suffer higher levels of disamenities such as congestion, high commuting costs, pollution, crime, etc. On the other hand, bigger cities enhance consumption by providing a larger amount of consumption amenities, such as restaurants, theaters, museums, shopping centers, and professional sports team. Consumption amenities are endogenous and depend on income level and urban scale, differing from other exogenous amenities such as natural amenities or historical amenities (Brueckner et al., 1999). Economies of scale and scope result in a greater variety of goods and services in bigger cities, which increases household utility level (Adamson et al., 2004).

In terms of spatial equilibrium, individuals are indifferent across locations. Hence, agglomeration economies should compensate for agglomeration diseconomies. More specifically, the effect of agglomeration on housing rents (and other disamenities) should be offset by the effect of agglomeration on productivity plus the effect on consumption. This leads to three distinct but related theoretical implications of agglomeration for consumption regarding urban wage premium, urban growth and household consumption pattern, which also in turn provide various empirical evidence on agglomeration economies in consumption.

4.3.2 Implication for Urban Wage Premium

The first implication is that if agglomeration economies in consumption exists, individuals would accept lower real wages to live in bigger cities to enjoy consumption amenities. Real income level reflects the net effect of agglomeration economies and diseconomies (Tabuchi & Yoshida, 2000). Literature on urban quality of life indicates that households would pay implicitly through labor and housing markets to live in a more amenable urban area (Blomquist et al., 1988). Hence, since consumption amenities compensate residents in large cities for high living costs, rent would increase with city size faster than nominal wage so that real wage decreases with city size.

Indeed, Glaeser et al. (2001) found that urban rents rise faster than urban wages in some large cities in both Europe and the United States, which implies that rising demand for those cities is partly due to urban amenities, among which consumption opportunities are the most obvious factor. Similarly, Albouy (2008) revealed a high willingness-to-pay to live near urban consumption amenities such as restaurants and bars. The results also indicated that one percent increase in the local wage level would increase housing costs by 1.5% even after controlling for natural amenities, which is suggestive of the benefits of consumption amenities.

In addition, some "consumer city" studies directly discover a negative relationship between real wage and city size and use this as evidence on agglomeration economies in consumption. For example, Tabuchi and Yoshida (2010) found evidence in Japan that doubling city size is associated with a 10% increase of the nominal wage but a 7-12% decrease of the real wage. These findings suggest that while agglomeration economies in production enhance productivity, cities also provide a large variety of consumption benefits. In line with this finding, Glaeser and Gottlieb (2006) argued that the urban resurgence in the 1990s in the United States is largely due to the increasing demand for the urban consumption amenities in large cities instead of the increase in productivity. They find that the relationship between real wage and population size is positive during the decline of big cities in 1970, but this relationship turns to be negative during the resurgence of cities in 2000. This implies that it is the increasing desire of people to live in large cities to enjoy abundant consumption opportunities that leads to the resurgence of cities in the United States.

More recent literature on the consumption-side explanation for the urban wage premium suggests that high urban nominal wage in large cities is in part due to high-skill workers disproportionately sorting into large cities driven by the taste for consumption amenities (e.g., Adamson et al., 2004; Lee, 2010). This is in clear contrast to the traditional explanation that focuses on the productivity-enhancing effect of agglomeration economies. The key idea is that because consumption amenities are normal and even luxury goods, wealthier households and more talented individuals have stronger preferences for a greater variety of consumption amenities in larger cities, and thus they are willing to pay more to enjoy large cities' consumption amenities than less-skilled and low-income workers. A testable implication would be that even as workers in larger cities may earn more in average than their otherwise equal counterparts in small cities, the urban wage differential should be decreasing with worker's skill and education level.

This implication is supported by Adamson et al. (2004), who found that net returns to education attainments decline with urban scale. Lower net returns to education taken together with a higher share of more educated workers in large cities imply that skill-biased consumption amenities, overwhelming productivity-enhancing effects, have drawn more-educated workers to large cities. This conclusion is mirrored in Lee (2010), who analyzed urban wage premium focusing on the healthcare sector. He found that high-skill healthcare workers are more concentrated in large cities and that the urban wage gap between large cities and small cities sharply decreases as skill level rises. The results even showed negative urban wage premium at top skill levels. For example, dentists and optometrists earn less wages in large cities than otherwise equal counterparts in small cities. These findings shed light on the important role of consumption amenities in large cities in enhancing urban quality of life, especially for skilled workers.

4.3.3 Implication for Determinants of Urban Growth

A growing number of literature on the determinants of city growth suggests that consumption amenities can be sources of agglomeration and encourage urban growth (Rosenthal & Strange, 2004). Agglomeration economies in consumption imply that a large urban scale would enhance consumption amenities, which in turn can make cities more attractive and promote urban growth. Glaeser et al. (2001) presented three important pieces of evidence supporting the importance of consumption amenities for city growth. First, Glaeser et al. (2001) found evidence of the rise of reverse commuting. The city-suburb commutes almost tripled between 1960 and 1990 in the United States, and the population growth was faster than employment growth in central cities. Reverse commuters work in suburbs and pay higher rents to live in cities to enjoy consumption benefits of cities. In addition, Glaeser et al. (2001) found in both the

United States and Europe that a city's population growth rate is positively associated with a large amount of consumption amenities, such as live performance venues and restaurants. Finally, Glaeser et al. (2001) also measured the level of the amenity by estimating the residual from the regression of housing prices on per capita income in a city. The analysis revealed a positive relationship between amenity level and population growth.

Similarly, Shapiro (2006) suggested that the concentration of skilled workers in a city encourages the growth of consumer services, such as restaurants and bars, which in turn makes the cities more attractive to migrants. This study found that about 40% of the employment growth is attributed to the increase in those consumption benefits. This pattern is in line with Carlino and Saiz (2008), who concluded that leisure consumption opportunities significantly facilitate population and employment growth in metropolitan areas in the United States. They found that bigger cities attract more leisure trips and doubling the number of leisure visit to an MSA is associated with a 2% increase in population and employment growth. In addition, Buch et al. (2014) reported that both the labor market condition and local-specific amenities have a significant impact on labor migration in Germany. They found that large cities have stronger fixed effects and thus are ceteris paribus more attractive than small cities for migrant workers. This is interpreted as evidence for the importance of specific consumption benefits of living in large cities for city growth, such as theaters and other cultural infrastructures that only exist in large cities.

4.3.4 Implication for Agglomeration Effects in Consumption

The most important implication of agglomeration effects in consumption related to this study is the role of large cities in enhancing consumption. It is not only because residents in larger cities ceteris paribus have higher demand for some certain goods, but also because a larger urban market would provide a greater variety of higher-quality and lower-price goods that fit consumers' tastes better.

From the consumer's perspective, literature on consumer behavior suggests that high consumption on some certain goods in large cities may be attributed to resident's high demand for social contact. Glaeser et al. (2001) argued that one of the main advantages of cities is social interaction and face-to-face contact among people. Compared to workers in small cities, Bacolod et al. (2009) found that workers in large cities have stronger cognitive and people skills, which are closely related to social interaction. Thus, it is plausible to believe that residents in large cities have a relatively high demand for goods and services that can facilitate social interaction. For example, Cosman (2014) suggested that bars, clubs, restaurants, and other private businesses exist primarily to facilitate social interaction in cities. Indeed, Banta (1989) found that large-city households spend more on out-of-home activities such as dining out, fees and admissions to events, movies, concerts, and out-of-town recreation, while small-city households spend more on television sets. Similarly, Glaeser and Gottlieb (2006) and Borck (2007) found that people ceteris paribus visit these places more frequently in large cities than small cities in the United States and Germany.

In addition, the idea that a consumer's purchase decision is significantly affected by peer influence and social comparison is a central feature of related literature on consumer psychology (e.g., Bearden & Etzel, 1982; Karlsson et al. 2004). These factors may have more significant influence on residents in large cities than residents in small cities, since large cities have much more face-to-face interaction opportunities. Peer influence would put pressure on consumers to buy what others buy, and aspiration level and social comparison mainly affect consumer's desire or wishes to purchase, rather than the perceived ability (income level) to it (Karlsson et al., 2005). Thus, because of higher average wages in larger cities, compared to their otherwise equal counterparts in small cities, consumers in large cities would consider more goods and services to be necessary consumption and may tend to purchase more luxury goods in order to project a favorable image, reduce cognitive dissonance, and avoid dislike and punishment (Karlsson et al., 2005; Sun & Guo, 2013). For example, Elliott and Leonard (2004) found that children prefer more decent trainers in order to fit in with their peers. Handbury and Weinstein (2015) found that households in large cities are less sensitive to sales and purchase more expensive and higher-quality varieties of the same good.

With regard to the supply side, large cities facilitate consumption mainly through four fundamental ways. First, because of fixed cost, products and services can only be viable if demand exceeds a certain threshold. Therefore, some products and services can only be provided in large cities. For example, Lee (2010) noted that museums and professional sports teams can be found in large cities but not in small cities. Schiff (2014) found that the rarest cuisines, such as Armenian and Austrian, can be found only in the biggest, densest cities in the United States. Hsu (2012) also suggested that industries with substantial scale economies can only be found in large cities where industries are more diverse.

In addition, the number-average-size rule, a recently discovered empirical regularity, states that the number and the average size of the cities where an industry is located follows a negative log-linear relationship, which implies that the rarest industry only exists in the largest city. Empirical evidence showed that the number-average-size rule holds well for three- and four-digit industries in the United States and three-digit industries in Japan (Mori et al., 2008; Hsu, 2012). These findings suggest that people with rare tastes would be better off in a large market.

Second, larger cities provide a greater variety of goods than small cities. For example, Schiff (2014) found that population size has a substantially positive effect on the restaurant variety in a city. The result is mirrored in broadcasting market (Waldfogel, 1999) and television market (Waldfogel et al., 2004), which suggested that consumers in larger market enjoy greater programming variety and more channels and that more people would listen to radio and watch television in larger cities. In addition, Handbury and Weinstein (2014) found that the number of varieties of groceries increases with city size. The results showed that doubling in city size leads to a 20% increase in varieties, and cities with highest varieties of groceries are the four largest cities in the United States.

Consumers' utility level would increase with the consumption variety in a city, and thus large-city consumers tend to consume more. For example, using liquor license data from Chicago, Cosman (2014) found that consumers have very strong preference for variety in nightlife venues and an additional new venue without music, dancing, or other amenities would raise consumers' welfare equivalent to a 13.5% increase in nightlife expenditure. Couture (2015) found that denser areas, such as downtowns, provide more choices of restaurants, which have a larger positive effect on gains from a higher level of variety than gains from shorter trips. Therefore, consumers are more willing to travel longer in denser areas to consume what fits their tastes rather than to travel shorter distance to consume what's nearby.

Third, bigger cities also provide higher-quality products, which would further facilitate consumption. George and Waldfogel (2000) found that newspaper quality, measured by page length and reporters per newspaper, increases with market size while the price does not change, because the quality of newspaper is tied to fixed costs. This leads to higher consumer satisfaction and higher subscription rates in larger cities. Moreover, Berry and Waldfogel (2010) argued that when quality is produced with variable costs such as restaurants, the entire distribution of restaurants fills out in larger market. That is, while the average quality of restaurants may not depend on city size, there are more both high- and low-quality restaurants in large cities.

Finally, consumers in large cities may also benefit from lower prices. While housing costs increase with city size, NEG model predicts that the price level of tradable goods is lower in larger cities due to two reasons (Krugman, 1991). First, because of trade costs, locally produced goods must be cheaper in local markets. Second, due to fixed costs and scale economies, larger cities produce more varieties than smaller ones. Using transaction-level data in the United States, Handbury and Weinstein (2014) found that the price index for groceries are lower in larger cities after controlling for purchaser characteristics, store amenities and differences in the number of varieties available.

In summary, although related studies on consumption-side benefits of large cities have pointed to the important role of large cities in enhancing consumption, the direct empirical evidence regarding the relationship between city size and consumption pattern has not accumulated significantly. One reason may be the scarcity of data on consumption pattern at the individual or household levels. To my knowledge, Glaeser and Gottlieb (2006) and Borck (2007) carried out the only rigorous empirical tests, and found a positive correlation between city size and different forms of consumption.

Using the U.S. survey data, Glaeser and Gottlieb (2006) reported that central-city residents visit concerts, restaurants, museums and movies more frequently than residents in suburbs, in small cities or outside cities. This suggests that cities facilitate different forms of entertainment. The conclusion is in line with Borck (2007) who found strong evidence of agglomeration effects in consumption in Germany. The results indicated that an individual's probability of going to bars, restaurants, cinemas, concerts and theatres and museums is significantly higher in large cities than that in small cities, even after controlling for the effect of sorting and individual heterogeneity. In addition, the analysis showed that while overall life satisfaction does not vary with city size, individuals in large cities experience higher satisfaction with consumption and lower satisfaction with housing, whereas the opposite holds for individuals in small cities. The results lend support to the equilibrium hypothesis that large-city residents should be compensated for high housing costs by agglomeration economies in consumption.

However, both studies focus on developed countries and use visit frequency to measure consumption instead of directly measuring the consumption expenditures. In order to fill the gap, this study directly examines the link between city size and various categories of household consumption expenditures in the context of China. Furthermore, since China is currently in the transition toward a consumption-driven growth, the results of this study shed light on how a more market-driven urbanization strategy would be more effective in facilitating consumption.

4.4 Data and Estimation

4.4.1 Data

The data used in this study comes from two sources. City population data comes from the China Urban Construction Statistical Yearbook in 2011, which publishes city permanent population in urban area. Permanent population of a city includes both registered population and migrants who live in the city over six months.

Household consumption expenditure data is from the China Household Finance Survey (CHFS) in 2011. This data set contains detailed information on household wealth, income, expenditure, demographic characteristics, etc. The baseline survey was carried out in 2011 directed by the Survey and Research Center for China Household Finance at the Southwestern University of Finance and Economics[17], and 2011 survey data is the only available dataset so far. The 2011 CHFS employs a stratified three-stage Probability Proportional to Size (PPS) random sampling design. More specifically, in the first stage, 2,585 counties/districts in 28 provinces (except Tibet, Xinjiang, and Inner Mongolia) are divided into 10 groups based on per capita GDP,

[17] Detailed information about this project can be found at http://www.chfsdata.org/ and Gan et al (2013)

and eight counties/districts are randomly selected from each group. In the second stage, four communities are randomly selected from each county/district based on the urban resident ratios. In the third stage, households are randomly drawn from each community based on local average housing price. The overall refusal rate is 11.6%, where the refusal rate is 16.5% in urban area and 3.2% in rural area. Finally, the 2011 CHFS covers a nationally representative sample including 8,438 households or 29,324 individuals in 66 cities.

4.4.2 Basic Estimation

This paper first uses OLS to estimate the relationship between city size and various measures of household consumption expenditure. The basic model follows Eq. (1):

$$y_i = \alpha s_i + X_i \beta + \varepsilon_i \qquad (1)$$

where the dependent variable y_i refers to household i's average monthly or annual consumption expenditure on specific goods or services, including:

- Dining out (monthly expenditure)
- Daily necessities, excluding food and clothing (monthly expenditure)
- Housekeeping services, such as nannies, cleaners, drivers, etc. (monthly expenditure)
- Entertainment, such as books, newspapers, movies, theater, dancing halls, etc. (monthly expenditure)
- Clothing (annual expenditure)
- Education, including schooling, training, fitness class, etc. (annual expenditure)
- Travel (annual expenditure)

- Healthcare, excluding expenditure on health insurance (annual expenditure)

It needs to point out that for respondents do not know or are unwilling to report family's total travel expenses, the CHFS reports a range of different values for household annual travel expenses. I replace this range with its mid-point.

s_i refers to city size. X_i is a row vector of household demographic characteristics variables, including household size, income, dummy variable for whether the income data is missing, and dummy variable for whether a household lives in rural areas. Table 1 gives summary statistics of household consumption expenditure variables and control variables.

<Table 1 here>

Next, I also add the region fixed effect to the basic model to capture the fixed effect of living in eastern regions, central region, or western region. In addition, the survey data also provides information on the actual environment where respondents live based on interviewers' observations rather than official census classification. If respondents live in municipal districts, interviewer reports whether they live in central city (central districts) or outskirts (suburban districts). If respondents live in town or rural areas outside municipal districts, interviewer reports whether they live in a large town, a small town or rural area. Thus, I also re-estimate municipal district subsample and town/rural-area subsample separately including these location fixed effects: city center vs. outskirts, or large town vs. small town vs. rural area.

4.4.3 Robustness Check

There are some critical econometric issues in analyzing the effects of city size on various household consumption expenditures. First, OLS estimation may be inconsistent because the survey data on household expenditure is left-censored to zero. There is a significant portion of households with zero expenditure on different types of consumption.

This study uses Tobit model to estimate the censored data as the presence of zero expenditures on consumption is regarded as an optimal choice made by households. For example, a household spend nothing on entertainment, because zero expenditure is optimal for that household. Tobit model assumes a single decision-making process that households choose the level of expenditure to maximize their welfare. Zero expenditure represents a corner solution to a constrained utility maximization problem, in which the preference for consumption is so low that spending nothing is the best for the household.

More specifically, Tobit model uses an unobserved latent household consumption expenditure variable y_i^*

$$y_i^* = \alpha s_i + X_i\beta + \varepsilon_i,\ \varepsilon_i \sim N(0, \sigma^2) \qquad (2)$$

where for household i, s_i is city size, X_i is a row vector of control variables, including household size, income, missing income data dummy, and location dummy variables. Then, the observed household expenditure y_i follows:

$$y_i = \begin{cases} y_i^*, & y_i^* > 0 \\ 0, & otherwise \end{cases} \qquad (3)$$

The probability of a household have positive consumption expenditure is

$$Prob(y_i > 0 | s_i, X_i) = \Phi(\frac{\alpha s_i + X_i\beta}{\sigma}) \qquad (4)$$

The expected consumption expenditure for a household with positive expenditure (uncensored observations) is:

$$E[y_i|y_i > 0, s_i, X_i] = \alpha s_i + X_i\beta + \sigma\lambda_i \qquad (5)$$

where $\lambda_i = \frac{\emptyset(^{(\alpha s_i + X_i\beta)}/_{\sigma})}{\Phi(^{(\alpha s_i + X_i\beta)}/_{\sigma})}$ is the inverse Mill's ratio, $\emptyset()$ and $\Phi()$ are the standard normal density and cumulative density functions, respectively. The OLS estimates would be biased by neglecting λ_i. In this study, the Tobit model is estimated by maximum likelihood (ML).

The second issue is related to the endogeneity of city size to household consumption expenditures due to simultaneity bias or reverse causality. There may be omitted variables and unobserved factors influence both city size and household consumption expenditure, hence, city size variable may be correlated with the error term. In addition, it's possible that households who originally have high consumption demand and expenditure are more likely to locate in large cities with high consumption amenities, leading to reverse causality.

This paper uses instrument variable for city size and implement 2-stage least square estimation (2SLS). Historic city population is employed to instrument the current city size. More specifically, the instrument variable is the urban population in 2003[18]. The rationale for this IV is that the distribution of city size persists over time (Davis and Weinstein, 2002).

[18] Population data earlier than 2003 does not available for all cities, because some cities in the sample were established in 2003 since when city population has been reported.

4.5 Empirical Results and Discussion

4.5.1 Main Results

Table 2-3 report the basic OLS estimation results of the analysis on household consumption expenditures on dining out, daily necessities, housekeeping services, entertainment, travel, education, healthcare, and clothing without and with region fixed effect respectively. The coefficients of household income in all regressions in both tables indicate a positive relationship between household income level and household consumption expenditures. This implies that all these consumption goods or services seem to be normal or even luxury goods, hence, demand for these goods or services increases with household income level. Moreover, household size seems to be an important determinant of consumption expenditures on daily necessities, travel, education, and clothing, while household size does not have significant influence on other consumption expenditures. The coefficients of household size suggest that larger families would spend more on daily necessities, travel and education. However, larger households is found to spend less on clothing for parents (household head and his/her spouse). One possible interpretation is that families with more children are more likely to spend more on the children rather than the parents.

<Table 2 here>

<Table 3 here>

Regarding the effect of city size, the estimation results of the full sample in Table 2-3 suggest following findings. First, the significantly positive coefficients of urban population variables point to the important role that large cities play in enhancing consumption. No matter region fixed effect is included or not, city size exerts significant and positive influence on all categories of household consumption expenditures. According to the results in Table 2, after controlling for household income and size, an increase of 10,000 residents in urban population is associated with an increase in monthly household expenditure on dining out, daily necessities, housekeeping and entertainment by 0.154 RMB, 0.035 RMB, 0.033 RMB and 0.032 RMB respectively. Moreover, an increase of 10,000 residents in urban population is associated with an increase in annual household expenditure on travel, education, healthcare, and clothing for household head, spouse and children by 1.088 RMB, 0.592 RMB, 0.155 RMB, 0.341RMB, 0.268 RMB and 0.315 RMB respectively.

Even though coefficients of urban population somewhat decreases after adding region fixed effect in Table 3, city size still show significant and positive influence in enhancing consumption expenditures. The results are in line with theoretic expectation that households in larger cities enjoy higher level of consumption amenities, and thus ceteris paribus consume more. I interpret this finding as the evidence that directly supports agglomeration economies in consumption.

Second, the rural area dummy variables have significantly negative coefficients in all household consumption expenditure regressions in Table 2-3, which indicates that households in rural areas seem to ceteris paribus have lower consumption expenditures than households in urban areas. This finding suggests lack of consumption possibilities in rural area compare with urban area.

Finally, the signs and magnitudes of the coefficients of regional dummy variables in Table 3 lead to the conclusion that household consumption expenditures are significantly higher in the more developed eastern region than the central and western region, except that regional dummy variables have insignificant effect on the household consumption expenditure on housekeeping services. The coefficients of eastern region dummy variables are all significantly positive and much higher than the coefficients of central region dummy variables, implying higher average household expenditures in eastern region, except the housekeeping services regression model. Since the eastern region is much more populous and is more attractive to migrant workers than the other two regions, the results reveal somewhat evidence of agglomeration for consumption at regional level.

Turning to the municipal district subsample, the estimation results in Table 4 substantiate the positive relationship between city size and household consumption expenditures. Urban population variables have significant and positive effect on all household consumption expenditures. Moreover, the results point to important differences between central city and suburbs. The positive coefficients of the city center dummy variables indicate that central-city households ceteris paribus have higher consumption expenditures than suburban households, which points to the specific consumption benefit of central cities. This result is in line with Glaeser et al. (2001) and Glaeser and Gottlieb (2006) who find higher consumption demand in central cities than suburbs.

<Table 4 here>

Table 5 reports the estimation results using town/rural areas subsample. The coefficients of all variables in the model of expenditure on housekeeping services are insignificant, which may be caused by little variation in the dependent variable in town/rural areas. Nevertheless, the results are suggestive of the importance of local market size. Despite housekeeping services, the signs and magnitudes of coefficients of location dummy variables in town/rural area indicate that large-town households ceteris paribus have higher expenditures than small-town and rural households.

<Table 5 here>

Surprisingly, in town/rural areas, the results only find significantly positive effect of city size on household expenditures on daily necessities and travel. However, results show negative effect of urban population on expenditures on education and insignificant effect on all other categories of consumption expenditures. One possible explanation might be related to the market size that a specific product or service covers in town/rural areas. Some goods or services provided in town or rural area may only serve a small local market (e.g. town, neighborhoods, villages), such as restaurants, education, cinema, healthcare, small shopping malls, etc. Furthermore, households living in town/rural areas may mainly consume these locally provided products or services due to limited access to the consumption amenities in municipal districts. Therefore, town/rural-area household consumption expenditures are more influenced by the size of local market, such as town size, while they are insensitive to or even negatively affected by the overall city size due to the competition between local market and regional market. Thus, the coefficients of urban population variables is insignificant or even negative while all the large town dummy variables have significantly positive coefficients, except that the housekeeping services regression model is insignificant.

Taken together, interpreting the estimation results leads to the main conclusion that large cities enhance household consumption. More specifically, there is a significantly positive relationship between city size and household consumption expenditures. Households also have higher consumption demand in urban area than rural area, and eastern region than western/central region. Furthermore, in municipal districts, households have higher consumption expenditures in central cities than outskirts; in town and rural areas, households have higher consumption expenditures in large towns than in small towns or rural areas.

4.5.2 Robustness Check

Robustness check addresses the econometric issue related to censored data and potential endogeneity of city size. The main conclusion is consistent and robust with different estimation methods.

Table 6 reports the results of ML estimation of Tobit model. The findings for the positive relationship between city size and household consumption expenditures are rather robust. Only the coefficient of urban population in the model of household expenditure on education becomes insignificant. All other household consumption expenditures are still significant and positively associated with urban population.

<Table 6 here>

Table 7 display the results of IV 2SLS estimation. The coefficients of urban population variables in all models substantiate the main findings for the positive effect of city size on household consumption expenditures. The model is exactly identified. As indicated by the test statistics at the bottom of the table, the hypotheses that urban population is exogenous is rejected, the applied instrument variable is relevant, and the weak instrument hypothesis is rejected. The coefficients of city size variables are all significantly positive. The IV estimation implies somewhat larger effects of city size on household consumption expenditures than OLS estimation, pointing to potential bias of OLS estimation resulted from reverse causality.

<Table 7 here>

4.6 Conclusion and Policy Implication

This study directly contributes to the emerging literature on agglomeration economies in consumption. In particular, by using the 2011 China Household Finance Survey (CHFS), the analysis has revealed clear evidence that large cities can enhance household consumption. The results suggest a positive relationship between city size and various categories of household consumption expenditures after controlling for household size and income level. In addition, households seem to ceteris paribus have higher consumption demand in urban areas than rural areas, in the more developed eastern region than in the western/central region, in central cities than in outskirts, and in large towns than in small town or rural areas. Potential OLS estimation issues related with censored data and endogeneity have also been addressed and the main conclusion is consistent and robust.

While larger cities in China seem to be more productive, they can also facilitate consumption. Both workers and consumers can benefit from co-locating with each other through agglomeration economies in both production and consumption. Thus, current urbanization strategies in China that encourage rural-urban migration to small cities and limit migration to large cities may lead to welfare loss from both production side and consumption side. A more market-driven urbanization process would be more efficient.

The analysis of this study is limited by the nature of the data. Different categories of household expenditures may be influenced by similar unobserved factors, which leads to loss of efficiency of OLS estimation. However, the limitation of available control variables and difficulties to satisfy identification conditions make it infeasible to apply econometric models such as seemingly unrelated regression or simultaneous equation models. Future research may shed more light on this topic by using different data.

Table 1. Summary statistics

Household consumption expenditure on	Obs.	Mean	S.D.	Min.	Max.
Dining out (monthly, RMB)	8361	301.37	2065.55	0	110000
Daily necessities (monthly, RMB)	8294	90.87	327.17	0	25000
Housekeeping services (monthly, RMB)	8432	24.75	415.23	0	30000
Entertainment (monthly, RMB)	8406	39.72	394.03	0	24000
Education (annual, RMB)	8397	3198.97	10812.2	0	424000
Healthcare (annual, RMB)	8420	345.32	1774.19	0	50000
Travel (annual, RMB)	8385	1669.69	5872.45	0	200000
clothing for household head (annual, RMB)	8345	1060.14	2577.32	0	50000
clothing for spouse (annual, RMB)	6872	972.27	2333.04	0	75000
clothing for children (annual, RMB)	5338	1139.45	1964.98	0	50000
Independent variable:					
2011 urban population (10,000)	8438	375.44	641.1	12.51	2347.46
household size	8438	3.48	1.55	1	18
household income (1,000 RMB)	8438	17.82	46.3	0	1202
Rural area dummy	8438	0.38	0.49	0	1
Instrument variable:					
2003 urban population (10,000)	8438	288.01	407.47	14.63	1312.7

Table 2. Household consumption expenditures and city size, full sample

	Dining out	Daily necessities	Housekeeping services	Entertainment	Travel
Urban Population	0.154**	0.0350***	0.0330**	0.0324***	1.088***
	(0.06)	(0.00)	(0.02)	(0.01)	(0.15)
Household size	-6.476	6.254***	9.373	-1.384	79.11
	(9.16)	(1.54)	(6.98)	(2.84)	(48.56)
Household income	5.120*	0.731***	0.479***	0.589***	25.32***
	(3.05)	(0.15)	(0.18)	(0.12)	(4.15)
Income data missing	58.02	10.74	34.93***	34.36***	549.7***
	(107.10)	(7.21)	(12.17)	(9.45)	(187.70)
Rural area	-143.8***	-23.40***	-21.96**	-35.24***	-771.4***
	(27.92)	(8.28)	(10.34)	(7.84)	(112.90)
Constant	196.8**	45.86***	-40.65	15.41	510.6**
	(99.89)	(6.97)	(28.02)	(13.50)	(252.40)
Observations	8361	8294	8432	8406	8385
R-squared	0.02	0.02	0.007	0.011	0.067
	Education	**Healthcare**	**Clothing for household head**	**Clothing for spouse**	**Clothing for children**
Urban Population	0.592**	0.155***	0.341***	0.268***	0.315***
	(0.26)	(0.04)	(0.06)	(0.07)	(0.06)
Household size	595.3***	-11.58	-52.55***	-42.60***	23.99
	(66.21)	(10.35)	(14.60)	(12.18)	(17.89)
Household income	20.28***	2.864***	15.73***	13.98***	5.296***
	(5.74)	(0.65)	(2.45)	(2.42)	(1.28)
Income data missing	-237.2	166.0***	-37.77	-10.43	86.24
	(293.30)	(46.56)	(97.11)	(98.09)	(68.73)
Rural area	-1,229***	-253.8***	-530.1***	-549.0***	-346.5***
	(199.70)	(40.60)	(51.65)	(44.66)	(49.50)
Constant	1,159***	277.0***	1,061***	994.5***	919.8***
	(349.40)	(60.88)	(119.20)	(118.50)	(91.81)
Observations	8397	8420	8345	6872	5338
R-squared	0.021	0.017	0.128	0.128	0.044

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Household consumption expenditures and city size, full sample with regional fixed effect

	Dining out	Daily necessities	Housekeeping services	Entertainment	Travel
Urban Population	0.130*	0.0308***	0.0284*	0.0259**	0.960***
	(0.07)	(0.00)	(0.01)	(0.01)	(0.15)
Household size	-5.032	6.316***	9.687	-1.092	87.56*
	(9.09)	(1.68)	(7.02)	(2.76)	(48.75)
Household income	5.059*	0.718***	0.468***	0.572***	25.00***
	(3.07)	(0.15)	(0.18)	(0.12)	(4.14)
Income data missing	58.17	10.61	34.98***	34.32***	551.0***
	(107.10)	(7.14)	(12.13)	(9.41)	(186.70)
Rural area	-133.9***	-20.72***	-20.25**	-32.13***	-721.4***
	(24.21)	(7.99)	(9.85)	(6.79)	(108.70)
Eastern region	61.93*	22.84***	8.842	22.04**	284.4**
	(35.35)	(4.29)	(7.41)	(9.51)	(125.50)
Central region	-32.20*	12.25	-10.73	-0.94	-242.0***
	(19.43)	(10.88)	(6.98)	(3.19)	(93.52)
Constant	178.5*	32.14***	-41.48	5.865	453.0*
	(91.13)	(6.66)	(29.75)	(10.99)	(264.10)
Observations	8,361	8,294	8,432	8,406	8,385
R-squared	0.02	0.02	0.008	0.012	0.068
	Education	**Healthcare**	**Clothing for household head**	**Clothing for spouse**	**Clothing for children**
Urban Population	0.461*	0.107***	0.307***	0.241***	0.239***
	(0.26)	(0.04)	(0.06)	(0.07)	(0.06)
Household size	599.4***	-9.149	-51.09***	-41.89***	21.03
	(66.00)	(10.26)	(14.61)	(12.40)	(17.71)
Household income	19.91***	2.739***	15.63***	13.89***	5.070***
	(5.73)	(0.64)	(2.45)	(2.43)	(1.27)
Income data missing	-239.9	165.7***	-38.16	-11.14	86.06
	(292.50)	(46.24)	(96.86)	(97.79)	(68.12)
Rural area	-1,157***	-231.7***	-512.4***	-532.2***	-295.1***
	(193.50)	(39.54)	(52.82)	(45.67)	(50.10)
Eastern region	568.4***	149.1***	132.8**	130.8*	372.8***
	(207.90)	(49.55)	(62.81)	(72.72)	(72.38)
Central region	168.1	-27.34	17.73	50.82	174.6***
	(190.00)	(41.96)	(54.25)	(61.38)	(55.65)
Constant	856.2**	218.2***	996.8***	921.5***	723.7***
	(346.90)	(71.79)	(129.80)	(134.50)	(106.30)
Observations	8,397	8,420	8,345	6,872	5,338
R-squared	0.021	0.018	0.129	0.129	0.049

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Household consumption expenditures and city size, municipal district subsample

	Dining out	Daily necessities	Housekeeping services	Entertainment	Travel
Urban Population	0.118***	0.0373***	0.0496**	0.0406***	1.241***
	(0.03)	(0.01)	(0.02)	(0.01)	(0.21)
Household size	-15.3	14.43***	41.08	5.409	393.3**
	(28.42)	(2.88)	(28.05)	(8.03)	(178.70)
Household income	5.595	0.620***	0.481**	0.575***	23.54***
	(3.63)	(0.15)	(0.21)	(0.14)	(4.69)
Income data missing	114.1	17.04	77.26***	50.62***	898.0**
	(149.90)	(10.47)	(25.03)	(16.55)	(358.20)
City center	233.9***	17.83	83.50**	41.42***	1,526***
	(41.32)	(11.96)	(35.21)	(14.01)	(331.20)
Constant	37.12	10.36	-215.8*	-42.21	-1,453*
	(125.00)	(15.51)	(123.50)	(31.10)	(818.60)
Observations	3,290	3,259	3,326	3,308	3,309
R-squared	0.03	0.049	0.015	0.014	0.052
	Education	**Healthcare**	**Clothing for household head**	**Clothing for spouse**	**Clothing for children**
Urban Population	0.960**	0.146***	0.393***	0.291***	0.378***
	(0.41)	(0.05)	(0.07)	(0.08)	(0.08)
Household size	1,191***	31.54	-67.78	-30.58	44.61
	(233.80)	(32.49)	(46.42)	(42.13)	(45.10)
Household income	18.60***	2.698***	14.32***	12.96***	4.546***
	(6.67)	(0.75)	(2.74)	(2.82)	(1.38)
Income data missing	-147.6	295.7***	-63.73	-36.3	226.3*
	(579.10)	(93.05)	(168.10)	(186.20)	(133.00)
City center	1,707**	200.7**	535.2***	388.6***	213.5
	(725.50)	(97.78)	(118.90)	(127.10)	(140.10)
Constant	-1,768	29.53	854.4***	798.0***	702.0***
	(1289.00)	(153.50)	(219.10)	(216.20)	(233.40)
Observations	3,317	3,323	3,276	2,560	1,949
R-squared	0.02	0.009	0.091	0.082	0.031

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Household consumption expenditures and city size, town/rural area subsample

	Dining out	Daily necessities	Housekeeping services	Entertainment	Travel
Urban Population	0.371	0.0286*	-0.00304	0.00787	0.577***
	(0.34)	(0.02)	(0.00)	(0.01)	(0.22)
Household size	9.172	4.597**	0.898	-0.808	49.68**
	(8.07)	(1.99)	(0.77)	(2.13)	(24.28)
Household income	1.139	1.281**	0.189	0.362*	25.53***
	(1.27)	(0.51)	(0.25)	(0.21)	(5.48)
Income data missing	-60.87	16.73	0.544	18.08**	321.7**
	(72.76)	(14.16)	(11.12)	(8.91)	(142.10)
Large town	403.8**	17.17*	9.835	69.83*	606.6***
	(201.00)	(9.69)	(12.00)	(41.56)	(170.70)
Small town	25.15	9.339	2.097	7.482**	438.7***
	(44.91)	(7.99)	(5.70)	(2.96)	(139.10)
Constant	75.57***	23.44	0.251	-5.42	27.88
	(25.92)	(15.53)	(12.68)	(6.32)	(159.80)
Observations	5,071	5,035	5,106	5,098	5,076
R-squared	0.011	0.008	0.001	0.005	0.06
	Education	**Healthcare**	**Clothing for household head**	**Clothing for spouse**	**Clothing for children**
Urban Population	-0.574***	0.0623	0.0423	0.096	0.0253
	(0.21)	(0.07)	(0.07)	(0.07)	(0.07)
Household size	465.9***	-2.51	-4.497	-18.14**	37.63**
	(45.60)	(6.81)	(9.07)	(8.07)	(17.81)
Household income	10.87**	2.033*	18.39***	14.70***	8.323***
	(4.42)	(1.18)	(4.42)	(3.30)	(3.03)
Income data missing	-564.5**	74.87	21.49	-11.36	39.85
	(222.60)	(45.54)	(113.00)	(86.04)	(93.03)
Large town	1,158**	397.3***	604.6***	561.8***	177.6**
	(451.70)	(106.60)	(92.55)	(83.93)	(73.50)
Small town	434.3**	105.7***	429.4***	393.0***	149.2**
	(212.40)	(39.63)	(72.23)	(55.91)	(67.21)
Constant	941.3***	48.29	304.1***	379.7***	592.2***
	(254.20)	(48.94)	(116.40)	(92.89)	(112.00)
Observations	5,080	5,097	5,069	4,312	3,389
R-squared	0.024	0.015	0.136	0.169	0.028

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Tobit estimates

	Dining out	Daily necessities	Housekeeping services	Entertainment	Travel
Urban Population	0.431***	0.0328***	0.936***	0.187***	2.309***
	(0.14)	(0.01)	(0.32)	(0.04)	(0.31)
Household size	37.82	9.570***	113.7	1.165	370.2***
	(27.75)	(1.26)	(115.40)	(9.89)	(100.70)
Household income	10.89**	0.750***	11.51***	2.646***	38.02***
	(4.32)	(0.16)	(3.31)	(0.62)	(5.63)
Income data missing	-829.0***	8.132	1,225***	48.23	-229.4
	(211.80)	(7.20)	(455.70)	(34.28)	(310.90)
Rural area	-1,157***	-22.83**	-2,459***	-630.9***	-720.9***
	(254.40)	(9.16)	(748.70)	(152.40)	(233.90)
Constant	-1,789***	17.2	-9,188***	-845.4***	-5,963***
	(541.50)	(11.13)	(2600.00)	(194.40)	(929.80)
Observations	8,361	8,294	8,432	8,406	8,385
Pseudo R-squared	0.0098	0.0013	0.0358	0.0214	0.0068
	Education	**Healthcare**	**Clothing for household head**	**Clothing for spouse**	**Clothing for children**
Urban Population	-0.186	0.691***	0.383***	0.273***	0.306***
	(0.41)	(0.12)	(0.07)	(0.07)	(0.06)
Household size	3,514***	-47.52	-19.32	-27.32*	24.58
	(385.60)	(53.09)	(18.92)	(16.39)	(20.32)
Household income	38.57***	12.31***	16.73***	15.08***	5.603***
	(8.47)	(2.17)	(2.55)	(2.53)	(1.32)
Income data missing	-4,461***	401.9**	-362.1***	-238.0**	10.89
	(643.70)	(197.80)	(109.20)	(112.90)	(74.22)
Rural area	-4,018***	-1,807***	-788.9***	-751.3***	-384.1***
	(628.70)	(248.00)	(68.77)	(66.15)	(55.86)
Constant	-15,654***	-5,045***	721.2***	723.1***	837.5***
	(2201.00)	(497.90)	(132.70)	(129.00)	(97.53)
Observations	8,397	8,420	8,345	6,872	5,338
Pseudo R-squared	0.0087	0.0079	0.0095	0.0093	0.0027

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7. IV estimate (instrument variable: urban population in 2003)

	Dining out	Daily necessities	Housekeeping services	Entertainment	Travel
Urban Population	0.191***	0.0423***	0.0448**	0.0398***	1.417***
	(0.05)	(0.00)	(0.02)	(0.01)	(0.19)
Household size	-4.787	6.587***	9.905	-1.049	94.01*
	(8.95)	(1.55)	(7.12)	(2.81)	(49.01)
Household income	5.021*	0.711***	0.448**	0.570***	24.45***
	(3.05)	(0.15)	(0.18)	(0.12)	(4.15)
Income data missing	56.2	10.39	34.34***	33.99***	533.4***
	(106.80)	(7.20)	(12.03)	(9.38)	(186.20)
Rural area	-133.6***	-21.45***	-18.75*	-33.24***	-682.0***
	(26.53)	(8.18)	(9.57)	(7.51)	(105.90)
Constant	175.8*	41.78***	-47.26	11.28	326
	(100.40)	(6.93)	(29.84)	(13.04)	(254.60)
Observations	8,361	8,294	8,432	8,406	8,385
R-squared	0.019	0.019	0.007	0.011	0.065
Test of endogeneity	0.0078	0	0.0019	0.0063	0
Underidentification test	0	0	0	0	0
Weak instrument test	29647.84	29254.16	29946.74	29822.09	29780.93
	Education	Healthcare	Clothing for household head	Clothing for spouse	Clothing for children
Urban Population	0.929***	0.208***	0.447***	0.358***	0.393***
	(0.33)	(0.04)	(0.07)	(0.07)	(0.07)
Household size	610.7***	-9.209	-47.70***	-39.63***	25.82
	(66.57)	(10.43)	(14.43)	(12.11)	(17.82)
Household income	19.39***	2.726***	15.45***	13.75***	5.095***
	(5.71)	(0.64)	(2.45)	(2.42)	(1.27)
Income data missing	-254.3	163.3***	-43.02	-16.17	81.61
	(292.20)	(46.37)	(96.85)	(97.86)	(68.49)
Rural area	-1,138***	-239.5***	-501.6***	-525.2***	-327.7***
	(193.00)	(39.95)	(52.03)	(43.69)	(49.25)
Constant	969.9***	247.6***	1,002***	950.3***	886.3***
	(351.20)	(61.17)	(117.20)	(115.80)	(90.31)
Observations	8,397	8,420	8,345	6,872	5,338
R-squared	0.02	0.016	0.128	0.128	0.044
Test of endogeneity	0.000	0.000	0.000	0.000	0.000
Underidentification test	0.000	0.000	0.000	0.000	0.000
Weak instrument test	29878.83	29996.08	29415.18	21825.94	14719.5

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Test of endogeneity reports the p-value of F test of excluded IV. Underidentification test reports the p-value for Kleibergen-Paap rk LM statistic. Weak instrument test reports the Kleibergen-Paap Wald rk F statistics.

Chapter 5: General Conclusion

Using China as a case study, this dissertation investigates the growth pattern and roles of large cities play in enhancing production and consumption through three empirical studies. The main conclusion of the three essays suggests that large cities are still dominant during rapid urbanization and there is strong empirical evidence of agglomeration effects in both production and consumption.

The first essay reveals a divergent growth pattern for large cities in China, which is consistent with both theoretic and empirical expectations. Large cities disproportionately attract rural-urban migration due to both market forces and other advantages related to the political significance of large cities. Excluding migrant workers in the count of urban population would result in an underestimation of the size and growth of large cities.

The second and third essays examine the market forces in development of cities in China, with a focus on the agglomeration effect in both production and consumption, respectively. The findings of the second essay point to the productivity-enhancing effect of industrial agglomeration. The results suggest that the mechanisms of agglomeration economies vary with industries and that regional industrial dominance limits agglomeration economies. Thus, a competitive regional industry structure is crucial to making the best of industrial agglomeration to promote productivity. The third essay points to consumption-side benefits of large cities by finding a positive relationship between city size and various household consumption expenditures. This finding lends support to the related “consumer city” literature.

The main conclusion of this dissertation raises some questions about the validity of the current national urbanization policies that try to control the growth of large cities, such as setting a ceiling population of megacities. First, these policies seem to have little influence in shaping the growth of large cities, as shown in the first essay. Furthermore, both production-side and consumption-side benefits of large cities, as indicated by the second and third essays, respectively, will keep disproportionately attracting a considerable portion of rural-urban migration in the next few decades, not to mention the political significance of large cities as discussed qualitatively in the first essay. Therefore, these growth-control policies may not only fail to address "urban diseases," but might also make these issues worse due to the mismatch between the unexpected population growth and insufficient provision of public infrastructure and services.

Second, policies encouraging rural-urban migration to small cities are in contradiction to the goals of current industrial transformation and upgrading and the transition to a consumption-driven economy, considering the importance of large cities in enhancing productivity, promoting innovation and facilitating consumption. It is the larger cities in China that are more productive and have higher consumption amenities. Thus, simply controlling the growth of large cities would result in a loss of these benefits of large cities.

How to address the "urban diseases" such as traffic congestion, high housing price, and pollution is not the topic of this dissertation, but the three essays show that the growth control strategies may not be the right choice, especially when China is in transition to a market-oriented economy. A more market-driven urbanization process is crucial for future sustainable economic development in China.

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