Just a Small Town with 10 Million People: Urban Agglomeration's Effects on Labor Productivity in Chinese Cities

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Abstract

This paper analyzes the impact of urban agglomeration on labor productivity across 262 prefecture-level cities in China, employing a variety of econometric techniques, including fixed and random effects models, two-stage least squares (2SLS), and two-step generalized method of moments (GMM). Contrary to expectations, our findings predominantly indicate a negative relationship between urban agglomeration metrics and real labor productivity. Specifically, while initial models suggested positive effects of population and real fixed asset investments on productivity, further analysis using dynamic models and first-order differences revealed that population density negatively impacts labor productivity. Moreover, the study finds that capital density and college ratio hold varying significance across models, suggesting complex interactions between education, capital investment, and urban development. These results challenge conventional wisdom on the benefits of urban agglomeration in developing economies and suggest the presence of negative agglomeration effects, such as congestion and infrastructural strain, in China's urban centers. The paper concludes with a discussion on policy implications, emphasizing the need for strategic urban planning and investment to mitigate these negative effects and foster sustainable urban growth.

Introduction

Since the end of the Cultural Revolution, China experienced an urban revolution. A significant top-down urbanization effort has led to a substantial influx of migrant workers, increasing the urban population from 12 percent in 1985 to over 50 percent in 2016 (Shen & Xu, 2016). Market-oriented reforms initiated by Premiers Deng Xiaoping and Jiang Zemin introduced preferential policies in China's eastern coastal regions to stimulate trade, resulting in a marked increase in foreign direct investments (Hayter & Han, 1998). This urban expansion increased the number of cities from 244 to 654 between 1982 and 2010 (Kam 2012). Following the announcement of the Belt and Road Initiative in 2013, which boosted foreign direct investment outflows, central and inland local governments commenced their modernization and urbanization initiatives (Song et al., 2018). This migration trend persisted despite the restrictive household registration system (hukou 户口), which hindered the full agglomeration of urban economies, leaving most Chinese cities undersized (Au & Henderson, 2006). Despite these political barriers, the rapid increase in urban population underscores the significant accumulation of knowledge and improvement in labor productivity over a short period. While literature exists on China's industrial and sectoral agglomeration, there is a noticeable gap concerning the impact of agglomeration on average urban labor productivity at the city level (He et al., 2015; Hu et al., 2016). Therefore, my analysis will focus on how urban agglomeration affects average labor productivity in over 262 cities and municipalities.

In exploring the dynamics of Chinese agglomeration effects alongside other developing economies, scholars have delved into various dimensions of agglomeration, including industrial concentrations, infrastructural impacts, and historical data assessments. China's population density also directly affects the level of government administrative powers, granting the status of prefecture-level cities (地级市). The increase in government powers also increases the likelihood of available data. Therefore, I will primarily focus on prefecture-level cities in my research. In the Data section of this paper, most of my observations come from coastal, developed cities rather than the spacious, less developed cities.

Measuring Agglomeration

Cities have long been the engines of economic growth, fostering innovation, commerce, and social exchange. One of the driving forces behind the success of cities is the phenomenon of agglomeration — the clustering of people and businesses. Identified over a century ago as Marshallian Localization Economies, agglomeration includes input sharing, labor pooling, and knowledge spillovers among firms (Marshall, 1890). However, the empirical relationship between agglomeration and labor productivity remains a subject of intensive debate and research due to the endogenous nature of labor productivity and agglomeration with their relations to higher earnings, which also leads to an increased level of education (Glaeser & Maré, 2001). In measuring agglomeration, urban economic literature has used the effect of agglomeration on productivity, wages, urban growth, and entrepreneurship (Rosenthal and Strange, 2004). Research in agglomeration attempts to answer the policy-making question of whether or not to subsidize agglomeration in receiving positive externalities (Glaeser & Gottlieb, 2008). This section of the paper examines various methodologies for measuring urban agglomeration, highlighting the debate between discrete and continuous metrics and exploring how different approaches yield diverse insights into urban economic dynamics.

The concept of agglomeration economies, fundamental to urban and regional economics, was initially proposed by Marshall (1890) and later elaborated by economists like Ohlin (1933), Hoover (1937), and Isard (1956). They identified different types of agglomeration economies: (i) large-scale economies, (ii) localization economies, and (iii) urbanization economies. Large-scale economies refer to the cost efficiencies a firm gains as it scales up, fostering a supply chain that supports large-scale firms. Localization economies pertain to industry clusters, offering specialized resources and industry-specific advantages. Urbanization economies emerge from the diverse clustering of businesses and people in cities, fostering innovation and knowledge exchange. The interactions in an urban area create opportunities for knowledge spillovers, innovation, and economic growth (Glaeser et al., 1992). My paper primarily focuses on urbanization economies, particularly those resulting from interactions between economic agents as the city population increases. As a result, I will explore different attempts to measure these interactions.

The debate over measuring the spatial dimensions of agglomeration economies centers on the complexities of defining geographical areas, whether by distance or political borders. For a long time, geographical proximities were somewhat overlooked in economic studies due to these challenges (Kominers, 2007). However, the advent of "New Economic Geography," initiated by Krugman in 1991, reintroduced a focus on spatial agglomeration, highlighting its prevalence and varying effects across industries (Krugman, 1991). Studies such as Ellison and Glaeser (1997) advanced this understanding by demonstrating that different industries exhibit distinct levels of agglomeration. To capture these interactions, Duranton and Overman (2002) outlined criteria for an effective agglomeration index: (1) comparability across industries, (2) control for overall agglomeration trends, (3) distinction between spatial and industrial concentration, (4) unbiasedness regarding the degree of spatial aggregation, (5) clear statistical significance testing, (6) computability from accessible data, and (7) a suitable model justification. Despite ongoing debates, no single index currently meets all these conditions, leading to inconsistencies in agglomeration studies and interpretations. Despite these complications, Kominers (2007) categorized two primary approaches: discrete and continuous. Discrete indices, like the Ellison-Glaeser index (EG index), assess agglomeration by analyzing data within distinct geographic or administrative units, such as cities or regions (Ellison and Glaeser, 1997). In contrast, continuous indices, exemplified by Duranton and Overman's K-density index, utilize continuous spatial data, measuring agglomeration based on the geographical proximity between firms or the density of firms across a landscape (Duranton and Overman, 2002). While continuous indices more thoroughly meet Duranton and Overman's criteria, computing them requires specialized data on firm locations and transportation efficiencies. Due to the macro nature of my paper, I will use a discrete index, similar to Glaeser's research.

Measuring urban agglomeration is also critical in understanding the relationship between urbanization and economic development. Traditional methods often represent this relationship by comparing urban population percentages with GDP per capita or growth rates. This approach, utilized in both international and regional contexts (Crédit Suisse, 2012; Zhu et al., 2012), tends to focus on urban concentration as a significant factor in economic development. Similarly, Henderson (2003) and Brülhart and Sbergami (2009) discuss urbanization shares and spatial concentration indices. However, these methods fall short of developing a measure that captures both the extent of urbanization and the level of concentration within urban areas, which are economies that arise from the dense concentration of businesses and people in cities. Lemelin et al. (2014) identified three properties for an effective urbanization measure: (1) to increase with the concentration of population and conform to the Pigou-Dalton transfer principle, where the rich will transfer some utility or income to the poor; (2) to increase with the absolute size of constituent local labor market areas; and (3) to be consistent in aggregation. My original measurement of the ratio of people living in the urban area to the total area fails as a measure of agglomeration with respect to all three criteria (Lemelin et al., 2014). Instead, they propose Eduardo Arriaga's method (1970, 1975) as an example of such a measure. It considers the expected size of the locality where a randomly chosen person resides, thus capturing the essence of urbanization and concentration without relying on arbitrary thresholds. This approach contrasts with traditional measures like the degree of urbanization or the Hirshman-Herfindahl index (HH index), which either struggles with urban-nonurban distinctions or overlooks the size variations in local labor market areas.

In my research on urban agglomeration, I focus on the concentration of population within a city rather than industries in the same sector pooling together in the same location. Arriaga's method, the EG index, and the HH index are all efficient indices for measuring the concentration of firms. However, when it comes to the city level, an index dependent on the concentration of population in major cities within a province does not yield the same analytical powers as industrial concentration. Although there are some cities with certain leading industries, the concentration of people does not depend on the name of the city but rather the size of it. Therefore, in considering urban agglomeration from the perspective of a worker, the most effective indices are still population density or simply population.

Spatial Equilibrium

In his book "Cities, Agglomeration, and Spatial Equilibrium," Edward Glaeser emphasizes a fundamental assumption for establishing spatial equilibrium: there are no gains from changing locations (Glaeser, 2008). He suggests starting with the Alonso-Muth-Mills model, which is simplified as a consumer problem. In this model, city inhabitants maximize their utility by balancing wages against commuting and rental costs. The model is as follows:

$$max_{c}U(C, L) \;=\; max_{d}U(W \,-\, t(d) \,-\, r(d)L,\; L)$$

The Alonso-Muth-Mills model, simplified to its basest form, is a constraint problem for the consumer, the working city inhabitants. The consumer maximizes wages minus commuting costs and rental costs multiplied by land, and the consumer maximizes units of land. Note that both the rental costs and commuting costs are functions of distance to the city center, which means that the consumers are indifferent between two different locations that have the same distance to the city center. In this model, the consumer chooses the distance away from the city center to maximize their consumption, which is wage minus travel costs and rental costs. If I simplify the model further, I can assume that everyone uses the same units of land. Then to take the first derivative of this constraint to d, I will have $r'(d)L \ =- \ t'(d)$, meaning that a consumer is indifferent between two locations, regardless of the distance to the city center, since rental rates and transport costs have an inverse relationship with each other, establishing and propagating the previous assumption that there are no rents to be gained with changing locations. Obviously, transport costs will not stay linear, and transport costs vary across different distances. For example, someone who lives half a mile away from their workplace will prefer to walk, while someone who lives fifteen miles away will prefer to drive. Glaeser then expands the "purest form of spatial equilibrium" to include transport costs where transportation may incur a fixed or variable cost for the consumer, car, or public transportation. With the expanded transportation calculations, Glaeser derives that a city with a more mature infrastructure and cheaper public transportation costs will reduce congestion, increasing the total metropolitan area and urban population. Essentially, congestion costs are the negative externalities of agglomeration effects. If a city fails to develop its infrastructure with an influx of population, then urban agglomeration yields more costs to the residents than benefits in labor productivity.

Theoretical Model

In order to explain the interaction between agglomeration and labor productivity, economists generally start with a Cobb-Douglas model. In measuring the output of farm labor in relation to the density of both population and capital, Ciccone and Hall (1996) propose the following model:

$$\frac{Q_s}{N_s} = \phi A_s^{\omega} D_s(\theta, \eta)$$

$$D_s(\theta, \eta) = \frac{\sum_{c \in C_s} (n_c h_c^{\eta})^{\theta} a_c^{1-\theta}}{N_s}$$

In this model, c is the measurement on a county level; s is the measurement on a state level; ϕ is the distribution of labor, which we assume is uniform (ϕ = 1); A is the Hicks-neutral technology multiplier, which improves the efficiency of both capital and labor equally; θ is the labor input; h is the average years of education; a is the rate of decreasing returns of an acreage; n is the total number of workers working in an acre; and η is the elasticity of education. Observe that Ciccone and Hall identified the main explanatory variables for labor productivity as n, h, a: employed worker density to a given land, education, and the decreasing rate of returns from capital. Expanding on Ciccone and Hall's model with a modern context, Zhang et al. (2012) built the following model:

$$\frac{Q}{L} = \Omega^{\lambda}\left(H^{1-\beta}\left(\frac{K}{L}\right)^{\beta}\right)^{\alpha\lambda}\left(\frac{T}{A}\right)^{\alpha\lambda-1}$$

Although Zhang et al. use different notations, the variables are similar: Ω is the total factor productivity of a city; α is the share of return from capital and labor; β is the distribution coefficient between K and L; T is the population; A is the area; λ is the external elasticity, measuring the agglomeration effectiveness, and its value is generally greater than 1, and H is the labor quality. $\alpha\lambda$ is the impact of urban scale density on labor productivity. Thus if $\alpha\lambda > 1$, then the agglomeration of population will increase the total return on the city. In adapting Ciconne and Hall's model to an urban focus, Zhang et al. distinguish the difference between the general population and the labor force, labeled T and L, respectively. Moreover, in Ciccone and Hall's model, n is the total number of workers working on the available acreage, while Zhang et al.'s model uses the opposite, where capital divides labor. In an urban model, it is difficult to distinguish between land and capital as factors of production as they are usually both measured as capital investment. Thus, Zhang et al.'s model reverses the two in order to calculate the density of capital per labor. Ciccone and Hall's model also measures the density of capital, but it measures how much capital the county has in accordance with the state ($\frac{n_c}{N_s}$). As a result, we can neglect this difference. In Zhang et al.'s regression, they elect to use the number of teachers in a city to determine "labor quality." Given the recent influx of migrant workers in China, I believe it is insufficient to use the number of teachers to measure the investment element per unit of land area, as it takes more time for human capital to come to fruition compared to physical capital. Thus, I propose to use the percentage of the population that has acquired some college degree within a city to measure this instead. Just as Glaeser and Resseger (2010) performed their analysis, I can use the proportion of BAs to determine the city's skill level with this metric. The model is as follows:

$$ln(\frac{GDP}{CPI*L}) = \beta_0 + \beta_1 ln(\frac{K}{CPI*L}) + \beta_2 ln(\%BA) + \beta_3 ln(\frac{Pop}{Area}) + \varepsilon$$

In this model, I have average urban labor productivity as the dependent variable measured by the total monetary output (GDP) of a city divided by the CPI of the city (real output) and the number of workers employed (L). The constant term is the result of logging the total factor of productivity to the power of external elasticity, measuring the positive or negative effects of agglomeration. The first explanatory variable is the real firm capital expenditure (K/CPI) divided by L. The second explanatory variable is the logged percentage of individuals with a college degree or above on the city level (BA). The final explanatory variable is the population within the city(POP). Together, my explanatory variables are the urban capital-labor ratio, the quality of labor, and the population. Similar to Zhang et al.'s model, β_3 it reflects the agglomeration effects on a city. With this model, I hypothesize that I will have findings similar to those of Glaeser and Resseger (2010), with their regression on the positive correlation between labor productivity and population while holding skill as a control. Since China, during this period, also witnessed a considerable rise in education levels (Kim, 2010), I believe that my findings in the first model will demonstrate a more significant correlation between population and labor productivity, with all βs being positive and β_3 being around 0.08, which is the coefficient in Glaeser and Resseger's paper (2010).

Note that in both models provided by Ciccone and Hall and Zhang et al., the models use discrete indices rather than the more axiomatically correct continuous indices in their research. At the same time, their concentration indices fall into the category that fails Lemelin et al.'s criterion. Consequently, my model also fails the Lemelin et al. criterion.

Data

The primary data source used in my paper was gathered from the China City Statistical Yearbook from 2006 to 2020. This large-scale yearbook is the most comprehensive statistical data published in China by the National Bureau of Statistics, presenting information for provinces, autonomous regions, and municipalities. In the China City Yearbook, I collected city GDP, the total registered population in the urban area, fixed asset investment, the city's total area, urban built-up area, and the CPI for each province and municipality. According to the National Bureau of Statistics, the calculation of fixed asset investments includes the following:

1. all construction investments above the threshold of ¥5 million;
2. private investments in the purchase or in construction of any equipment, tools, types of machinery, assembly, or construction projects with no threshold;
3. public investments into constructing basic infrastructures, including types of transportation, public facilities, and means of communication;
4. any foreign direct investments (including Hong Kong, Macao, and Taiwan) received, including the purchase of foreign equipment, materials, and technology;
5. outward foreign direct investments, including investments made with foreign profits, excluding domestic foreign currencies;
6. all types of debt, including public sector, private sector, and foreign; and finally, all other fixed assets investments outside of the aforementioned methods, including social fundraising, personal funds, and charities.

The original data presents fixed asset investments in ¥10,000, GDP in units of ¥100 million, the population in 10,000 people, areas in squared kilometers, and CPI as holding the previous year as 100. However, the same data source only presented the number of people who were self-employed or employed by small, private firms, and it presented education levels as the number of schools, number of employed teachers, and number of students currently enrolled in each level of the education system. To find a more concrete source for employment and education levels, I used the provincial-level yearbooks. For each of the cities represented, their respective provinces publish annual yearbooks, presenting the total employment in urban areas and the number of individuals that have a bachelor's degree (本科) or a Chinese equivalent of an associate's degree (专科). Total employment is presented in units of 10,000 people, and college attainment is also presented in units of 10,000 people.

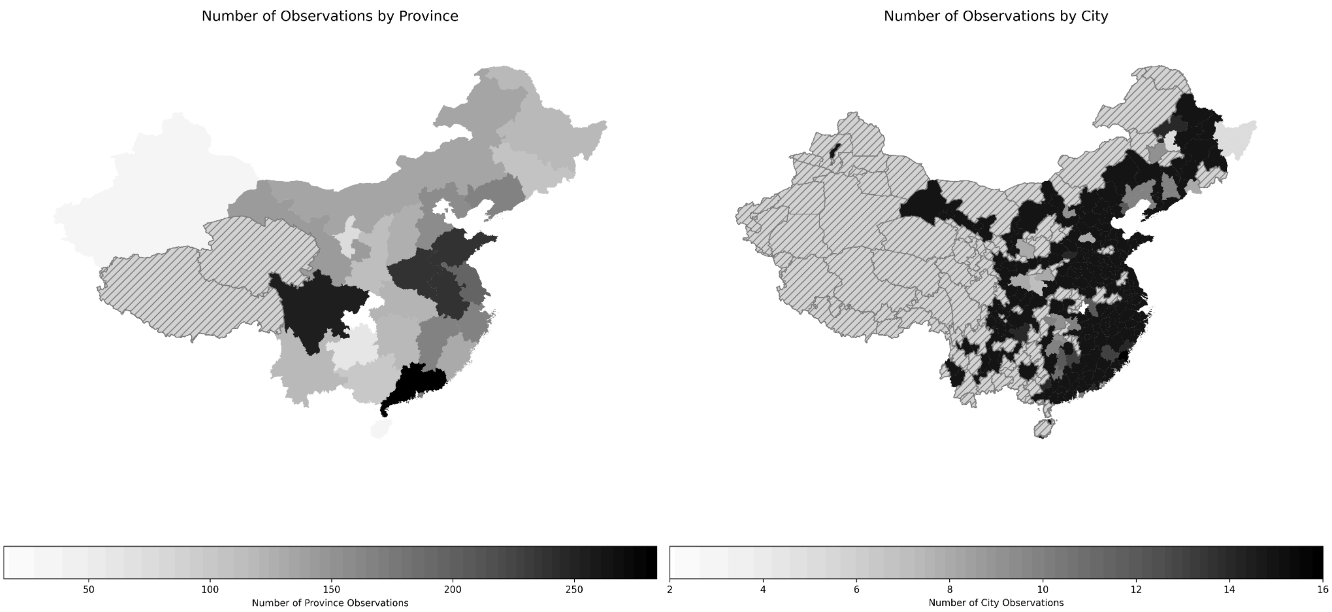
Putting everything together, I have data for 262 provincial-level cities (直辖市) and prefecture-level cities (地级市) across 22 provinces, 3 autonomous regions, and 4 municipalities for the span of 15 years from 2006 - 2020. China has a total of 34 province-level administrative divisions:

- 23 Provinces
- 5 Autonomous Regions
- 4 Municipalities (Beijing, Shanghai, Chongqing, Tianjin)
- 2 Special Administrative Regions (SARs) (Hong Kong, Macao)

Table 1: Descriptive Statistics for All Cities From Years 2006 - 2020

	GDP	Capital	Employed	Population	College	College Ratio	Adjusted CPI	Area	Developed Areas
count	3690.00	3690.00	3690.00	3690.00	3690.00	3690.00	3690.00	3690.00	3690.00
mean	21993078.47	13530872.45	273.19	459.72	9.19	1.65	134.86	2543.12	139.01
std	34078309.10	17707986.84	221.61	348.45	16.04	1.92	30.44	3275.86	193.98
min	519300.00	177800.00	4.50	19.37	0.01	0.00	100.91	97.00	6.55
25%	5882300.00	3799189.49	135.20	250.36	1.52	0.51	114.16	1024.35	48.20
50%	11605700.00	8054585.21	214.46	373.17	3.52	0.97	130.08	1800.14	75.59
75%	23718750.00	15725012.10	348.00	574.74	8.16	1.84	142.85	2868.00	139.76
max	389633000.00	219844125.70	2143.70	3209.00	130.71	12.76	503.85	43263.52	1565.61

Since the China City Statistical Yearbook does not provide the data for the two SARs and a non-mainland province, I will exclude them from my dataset. There is also a lack of education data in 2 autonomous regions, Tibet and Qinghai, which means I will exclude both of those provinces too. The rest of the provinces, autonomous regions, and municipalities are all represented in my dataset. Out of the provinces, Guangdong and Sichuan have the most observations at 284 and 255, respectively, while Xinjiang and Hainan have the least observations at 30. Together, I have 3,692 total observations.



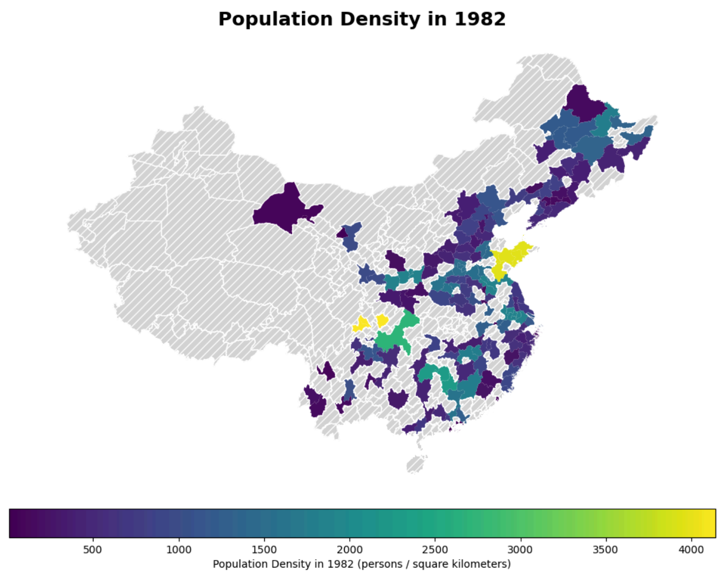
In gathering data for my instrumental variable, I used IPUMS International[1] to collect the population density from the Chinese census in 1982, the *Third National Population Census of the People's Republic of China* officially. This census came at a time right after a major regime shift in China, and the last census was conducted in 1964. It was also a time when China had recently

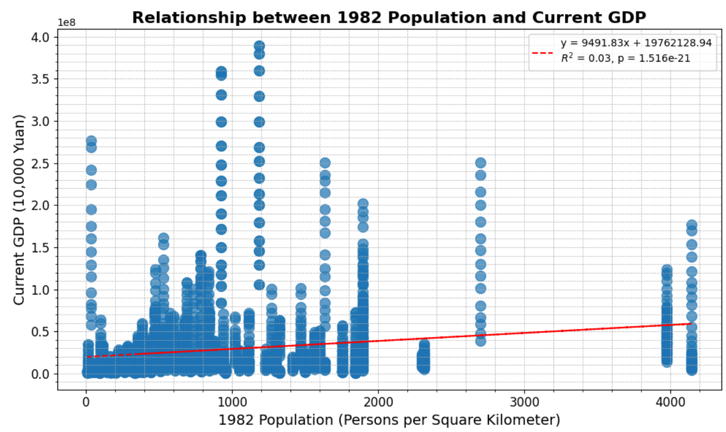
Table 2: Descriptive Statistics Across all Cities for 2010 and 1982 Population

	GDP	Capital	Employed	Population	College Ratio	Adjusted CPI	Area	Developed Areas	1982 Population
count	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00
mean	19860896.39	10667556.97	306.40	524.06	1.70	127.82	2397.69	149.82	952.10
std	28379227.06	12240609.41	246.84	407.16	1.87	25.78	3203.07	209.89	887.06
min	1040300.00	473714.00	12.60	23.19	0.11	109.43	97.00	13.10	8.10
25%	6285450.00	3784010.00	144.69	264.34	0.57	115.05	820.10	49.00	367.33
50%	9212700.00	6294256.00	250.83	446.10	1.00	116.54	1537.00	76.43	689.47
75%	21625600.00	10701956.00	402.05	675.42	2.00	119.94	2636.38	152.29	1310.27
max	179154000.00	69348000.00	1912.10	2885.00	9.91	293.14	26041.15	1231.30	4141.32

implemented the One-Child Policy, leading to a birth rate that is very similar to the death rate. There are also many cities from the same province that yielded the same number for population

[1] IPUMS International. (n.d.). International.ipums.org. https://international.ipums.org/international/index.shtml





densities, either a coincidence or lack of authentication. Although riddled with problems and controversies, this may be the only official and the most trustworthy source of information for the Chinese population before the urban migration occurred. At the same time, even if the numbers are inherently problematic, they are still skewed in a way that can potentially demonstrate the amenities of these historic cities. The original dataset includes population densities for 319 cities, but most of them have different names or are under other cities' jurisdiction today. After cross-referencing the data, I was able to obtain 183 population densities from 1982.

Indeed, in a country where market reforms and political powers sway the migration of the population, there may be better metrics than historical population densities to determine whether a city is amenable (Au & Henderson, 2016). In my considerations from the macro level, the two previous surveys consist of more flaws and inconsistencies than the 1982 survey. And in 1982, market reforms had just started to take shape in China before the migration happened. As China shifts away from the agricultural and industrial sectors, historically, large cities may not hold their importance. As the figure above shows, the coefficient between the 1982 population and current GDP may be positive, but the R-square value is almost negligible at 0.03. I will later demonstrate the correlation between the historical population and the current population.

Preparing the Data

For the missing data in some entries, either due to a later removal of the data or the discontinuation of collection of certain metrics, I cross-referenced other sources such as the Wind Financial Terminal[2], the Choice Terminal[3], and CEIC Data[4]. Although these three sources may present additional information compared to the original yearbooks, the original data presented by these three sources still originate from government statistical yearbooks; hence, some data from the yearbooks may be removed from view at a later date. For the remainder of the missing data, I have removed entire rows. This leads to some cities not having the complete panel data as a result. Since the discontinuation of collection happens on a provincial level, many cities from the same province will have missing data from the same years. This also leads to some provinces being more represented in the dataset than others, as previously indicated.

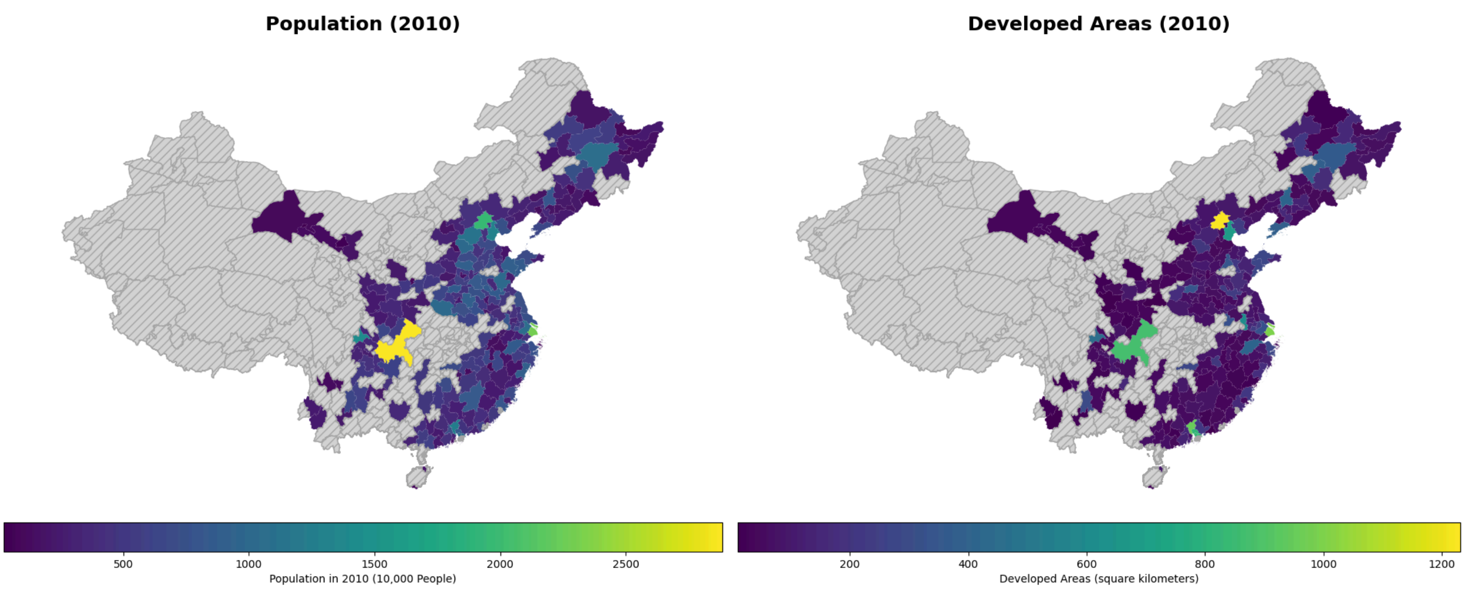
After correcting for the fact that some data may be missing, I realized that there may be some discrepancies between my data and the data freely available to the public. A case in point involves the college attainment rate data. This data, gathered from annual surveys published by local authorities in each province, indicates that approximately 33 million urban Chinese citizens hold bachelor's degrees or higher in 2020. In contrast, a 2023 government-published news article states that over 200 million Chinese citizens possess bachelor's degrees and above. This discrepancy is worrisome, and investigation through the Wind Terminal yields limited

[2] Wind金融终端, Wind Financial Terminal, https://www.wind.com.cn/mobile/WFT/en.html.
[3] Choice金融终端, East Money Choice, https://choice.eastmoney.com/.
[4] CEIC Data, "China Economic Database," CEIC, https://www.ceicdata.com/en/products/china-economic-database.

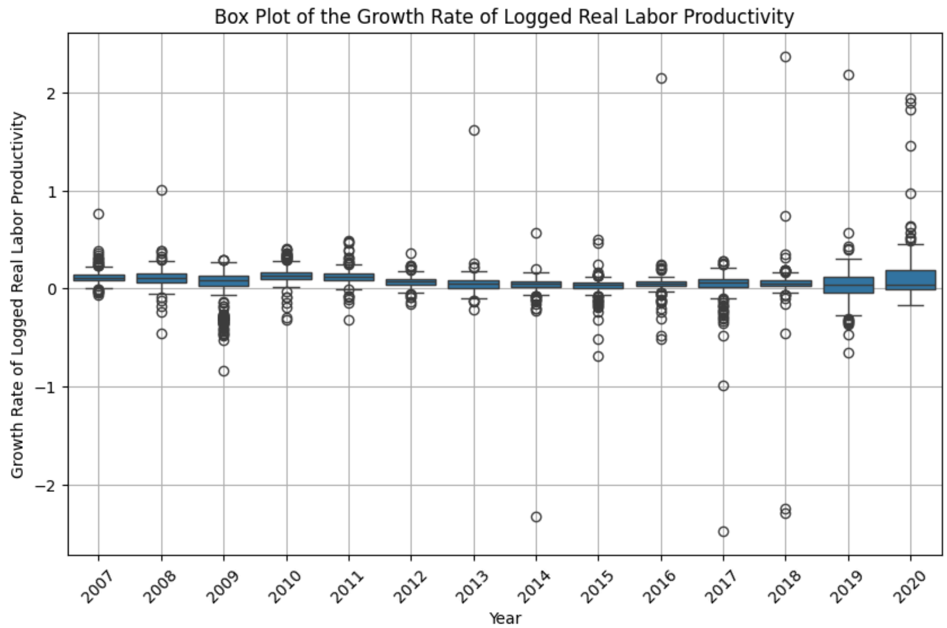
information, offering only three data points on China's college attainment rate for 2000, 2010, and 2023. Although such a difference may mislead the magnitude of the coefficient for college ratios, the consistent growth rate in comparison to the article’s data throughout the dataset infers that the discrepancy will not hinder the significance of college ratio as an independent variable.

In China, administrative divisions have five levels: province, prefecture, county, township, and villages. Prefecture-level cities almost always include counties, county-level cities, and districts. For example, in Suzhou, Jiangsu, there are four county-level cities, also known as satellite cities, four suburban districts, and one city proper. Although the county-level cities usually have greater administrative power, land area, and population, they are usually less densely populated than the districts within the prefecture-level city. Note that in America, a county is more significant than a city, where a city is usually represented only by the urban areas surrounding the city center. In China, a prefecture-level city is the next level of division after provinces. As Chinese cities rapidly grow, their administrative powers increase with them, corresponding to a more significant number of county-level cities under their jurisdiction. This corresponds to a violent inconsistency in the cities’ reported areas as they may lose or gain control of counties. As a result, I created a variable named Adjusted Area in my dataset, where the Adjusted Area is simply the area of the city’s most recent report, which is in 2020. I will later discover that the adjustment still does not help the cities’ reported areas’ explanatory power. The National Bureau of Statistics defines the urban built-up area as the city’s administrative area that has been developed and has public facilities. This area corresponds to the urban areas that are within the prefecture-level city, meaning that it contains both the city proper and the metropolitan areas of the county-level cities. This number, although it may see significant fluctuations, remains steadier than the cities’ legal areas.

To take the population density using population and urban built-up areas may seem improper as this density number reports the population that is outside of the urban built-up area. Taking the population density with the reported area may be even more nonsensical; however, cities that have sizeable uninhabited land will report an extremely small population density (cities like Chongqing). Furthermore, a city's reported area greatly varies due to various political and unique economic factors, and a city's urban built-up area does not have a specific metric as to what qualifies as a built-up area. Keeping this in mind, we may have to alter our metrics for agglomeration. As the figures show below, developed areas demonstrate the closest match to the population.



To address the original derivation of CPI, I calculated the CPI by compounding each year's CPI data with the last. This results in each year's CPI holding 2005's CPI as 100 since my dataset began in 2006. As a result, all monetary calculations that involve CPI yield values in the 2005 Chinese Yuan. I also corrected each variable's units where GDP and fixed asset investments are in units of ¥10,000, employed, college attainment, and the population is in units of 10,000 people, and college ratio as a percentage of college attainment overpopulation.



Summary Statistics of Key Variables

	LN Real Labor Prod	LN Real FAI	LN College Ratio	LN Pop	LN Pop Per Developed Area
count	3690.00	3690.00	3690.00	3690.00	3690.00
mean	10.68	10.23	-0.02	5.90	1.44
std	0.72	0.80	1.06	0.70	0.73
min	7.60	7.00	-5.56	2.96	-1.06
25%	10.20	9.75	-0.68	5.52	0.91
50%	10.69	10.32	-0.03	5.92	1.47
75%	11.18	10.76	0.61	6.35	1.98
max	13.56	12.70	2.55	8.07	3.69

Empirical Results

I will first proceed with the model as I described in the previous discussion. The model is as follows: $ln(\frac{GDP}{CPI*L}) = \beta_0 + \beta_1 ln(\frac{K}{CPI*L}) + \beta_2 ln(\%BA) + \beta_3 ln(\frac{Pop}{Area}) + \varepsilon$

In my regressions, the variable name LN Real Labor Prod refers to the log of GDP / Employed and adjusted for inflation, LN College Ratio refers to the log of the statistic college ratio, LN Population refers to the log of the statistic population, LN Pop Per Developed Areas refers to the log of the ratio of prefecture population over the developed areas, and LN Real FAI refers to the real financial asset investment (Capital) / Employed and adjusted for inflation. I will first focus on the production function derived from earlier in the paper; then, I will discuss the shortcomings of a linear regression in front of panel data that spans a great variety of cities. Finally, I will demonstrate my findings after implementing instrumental variables and taking all my variables' year-on-year differences.

Table 3: Three Regression Outputs with Different Agglomeration Metrics

	Dependent variable: LN Real Labor Productivity		
	Population Per Developed Area	Population Per Adjusted Area	Population
LN College Ratio	0.018**	0.104***	0.095***
	(0.008)	(0.008)	(0.009)
LN Pop			0.038***
			(0.012)
LN Pop Per Adjusted Area		-0.006	
		(0.009)	
LN Pop Per Developed Area	-0.331***		
	(0.014)		
LN Real FAI	0.506***	0.630***	0.640***
	(0.014)	(0.012)	(0.012)
const	5.974***	4.221***	3.910***
	(0.161)	(0.121)	(0.157)
Observations	3690	3690	3690
R^2	0.689	0.629	0.630
Adjusted R^2	0.689	0.628	0.630
Residual Std. Error	0.400 (df=3686)	0.437 (df=3686)	0.437 (df=3686)
F Statistic	2787.645*** (df=3; 3686)	1931.209*** (df=3; 3686)	1918.903*** (df=3; 3686)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard Errors are heteroscedasticity robust (HC2)

First, I will examine the basic regressions in Table 3 without any techniques used to correct for the autocorrelation influenced by the year variable. The three promising regressions in Table 3 show the difference in the agglomeration metrics. By comparing the R-squared values, we can see that the Adjusted Area has essentially no explanatory power over the independent variable. So, I will rule out Adjusted Area as a worthy explanatory variable from this point. The estimated coefficients of the OLS regression show almost statistical significance for all independent variables and the constant variables. The positive elasticities between real fixed asset investments and real labor productivity imply that a one percent increase in real fixed asset investments corresponds to around 0.506 - 0.640 percent increase in labor productivity. Since the elasticity is below 1, the relationship conveys below-constant returns to scale. A similar elasticity between ln(capital/ employment) and ln(GDP/ employment) in 1997 was 0.452(0.0398) and 0.324(0.0645) across all prefecture-level cities in China (Au & Henderson, 2006). As expected, the logged population variable has a positive coefficient. The coefficient is statistically significant, but the effect is quite small. A similar regression in American cities shows the following coefficients: Log(Output per Worker) = 9.49 (0.11) + 0.098 (0.01) Log (Population) + 1.18 (0.14) College Ratio, R squared of 0.47 (Glaeser & Resseger, 2010). Although I have statistically significant explanatory variables, I observe that the population density (calculated by the population over the developed areas) has a negative effect on labor productivity, while population, without the constraint of area, shows a positive correlation. Let me try this regression again, where we separate the two contrasting variables and determine whether we can observe the agglomeration effect.

After separating the two variables in Table 4, we can see that the absolute magnitude of the coefficient for the Developed Area is stronger than that of the population. Furthermore, the coefficient for population, a metric that is positive in Table 3, turns out to be negative when I separate the two variables. As I established

Table 4: Regression Output Separating Population and Areas

	Dependent variable: LN Real Labor Prod
LN College Ratio	-0.038***
	(0.009)
LN Developed Area	0.415***
	(0.015)
LN Pop	-0.246***
	(0.014)
LN Real FAI	0.510***
	(0.014)
const	5.064***
	(0.165)
Observations	3690
R^2	0.711
Adjusted R^2	0.710
Residual Std. Error	0.386 (df=3685)
F Statistic	2190.919*** (df=4; 3685)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard Errors are heteroscedasticity robust (HC2)

earlier, one possible explanation for this is that developed areas increase with the local government's wealth, which directly corresponds to the GDP. Assuming from Table 3 and other works that there are agglomeration effects where the increase in population will increase labor productivity, which increases the GDP, the local government will establish more developed areas as a result of the influx in population. Table 4's coefficients may tell a story that a city's local government develops their cities faster than the population can increase. But another story behind the scenes may come from the possibility that time and place are influencing every variable. Indeed, a city that experiences a growth in GDP or labor productivity will attract more workers and force a greater investment from the government to build public facilities (Glaeser et al., 1992). Thus, I will restate the former story where the Developed Area can serve as a metric for infrastructure, which $\frac{Pop}{Area}$ becomes a measurement for congestion, similar to a $\frac{Roads}{Capita}$ variable (Au & Henderson, 2006). If positive, the city experiences a positive agglomeration effect where increasing population will lead to greater labor productivity. If negative, the city experiences a negative agglomeration effect similar to congestion, where decreasing population or increasing development will increase labor productivity. However, in the unfortunate case, there is a third story: the Developed Area variable is also as untrustworthy as the other area variables. To appear competent and demonstrate a growing economy, local governments may artificially exaggerate this statistic. On the other hand, political rivalries may understate this statistic. Keeping all three possibilities, I will test the one that is the most possible with the data I have by including time and location fixed effects.

Static Model

Table 5: Static Models Comparison

	Regression with Population		Regression with Population 'Density'	
	Fixed Effects	**Random Effects**	**Fixed Effects**	**Random Effects**
Dep. Variable	LN Real Labor Prod	LN Real Labor Prod	LN Real Labor Prod	LN Real Labor Prod
Estimator	PanelOLS	RandomEffects	PanelOLS	RandomEffects
No. Observations	3690	3690	3690	3690
Cov. Est.	Robust	Robust	Robust	Robust
R-squared	0.4568	0.9777	0.4741	0.9563
R-Squared (Within)	0.7367	0.7138	0.7617	0.4760
R-Squared (Between)	0.6845	0.9960	0.6820	0.9947
R-Squared (Overall)	0.6847	0.9957	0.6823	0.9942
F-statistic	956.12	5.394×10^4	1025.1	2.69×10^4
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
LN Real FAI	0.5085***	0.5723***	0.4843***	0.9258***
	(20.154)	(59.102)	(18.907)	(239.88)
	(0.0000)	(0.0000)		
LN Pop	-0.0871*	0.8023***		
	(-1.7671)	(45.917)		
	(0.0773)	(0.0000)		
LN College Ratio	-0.0170	0.0161	-0.0326**	-0.0611**
	(-1.6126)	(1.1885)	(-3.1374)	(-3.7699)
	(0.1069)	(0.2347)		
LN Pop Per Developed Area			-0.2046***	0.5165***
			(-9.8873)	(27.194)
Effects	Entity, Time		Entity, Time	

Note: *p<0.1; **p<0.05; ***p<0.01. The following stats are for the fixed effects models: Entities: 262, Avg Obs: 246.00, Min Obs: 224.00, Max Obs: 260.00. Time periods: 15, Avg Obs: 14.084, Min Obs: 2.0000, Max Obs: 15.000. Entity describes the unique province and city combinations. Time periods are in years. With a Hausman test statistic of 403.546 (df = 2) and 4937.225 (df=2) for the regressions on population and population 'density' respectively, both with a p-value of 0.0, the test results are significant, suggesting that there are systematic differences between the fixed effects (FE) and random effects (RE) model estimators. This implies that the null hypothesis (that the difference in coefficients between the fixed and random effects models is not systematic) is rejected. The FE model provides consistent estimates under unobserved heterogeneity correlated with the included regressors,

To test for fixed effects, I will first use static models to determine whether there are systematic differences between the fixed effects and random effects. In Table 5, I used two models to test both of the variables of interest: population and population per developed area. The fixed effects include dummies for all 15 years and 262 unique province-city combinations. Observe that the coefficients for LN Real FAI are positive for all regressions, and the coefficients for LN College Ratio are mixed, ranging from negative to statistically insignificant. Under the Hausman test, both regressions display systematic differences between the FE and RE models. However, due to the many underlying assumptions of the Hausman test, I cannot immediately reject the findings from the RE model (Baltagi 2008). By comparing the R-squared values, I can assume that my previous model may suffer from overfitting as the variables display less explanatory power under fixed effects. Both population density and population have negative effects on labor productivity, and population density has a greater statistical significance. A negative coefficient for population suggests that the average city has exceeded the spatial equilibrium, and a negative coefficient for population density suggests that negative agglomeration effects outweigh the positive ones.

Dynamic Model

It is apparent that population, labor productivity, and developed areas are correlated. I now consider using 2SLS and GMM to estimate the production function, using instruments to limit the effects of multicollinearity. The other variables in the dataset may also be multicollinear, but in measuring agglomeration effects, I will use the historical population from major cities as an amenity metric for these cities. Since fixed effects are present, I will conduct the 2SLS with just

Table 6: Validity of 1982 Population as an IV

	2010 Population	**2010 Population 'Density'**
R-squared	0.387	0.068
Adj. R-squared	0.383	0.063
F-statistic	114.1	13.14
Prob (F-statistic)	5.76e-21	0.000375
Log-Likelihood	-160.84	-204.60
AIC	325.7	413.2
BIC	332.1	419.6
Coefficient		
Const	3.3243***	0.3606
	(0.255)	(0.324)
	[0.000]	[0.267]
LN 1982 Population	0.4197***	0.1809***
	(0.039)	(0.050)
	[0.000]	[0.000]
Omnibus	7.701	17.031
Prob(Omnibus)	0.021	0.000
Durbin-Watson	1.625	1.629
Jarque-Bera (JB)	13.654	5.820
Prob(JB)	0.00108	0.0545
Skew	0.087	0.042
Kurtosis	4.327	2.130
Cond. No.	39.1	39.1

Note: ***p<0.01. Standard Errors are in parentheses. Standard Errors assume that the covariance matrix of the errors is correctly specified. P-values are in brackets. Population 'Density' refers to the population per developed area.

2010 data and the GMM with the entire panel. I chose 2010 to perform this analysis because my dataset includes the most data in the year 2010. To test if the 1982 population density is a valid instrument, I use a simple linear regression between the instrument and the agglomeration metrics. As the F-statistics are both greater than 10, there exists a correlation between historical population densities and current population densities and population. In Table 7, I use two different models to demonstrate the difference in the two agglomeration metrics. On the left, the model assumes the population to be endogenous, casting a prediction of the population using 1982 population density. On the right, the model assumes population per developed area to be endogenous. Both models have identical goodness-of-fit, displaying the same test statistics on both sides of the model. The main difference between the two comes in the coefficients. Although both sides of the model display negative coefficients for the agglomeration metric, the elasticity between population per developed area has a more significant negative effect on labor productivity. Both models agree on the significance and positive effects of Real FAI but disagree on the importance of human

Table 7: IV2SLS Models

	Pop as Endog	**Pop 'Density' as Endog**
R-squared	0.584	0.584
Adj. R-squared	0.577	0.577
F-statistic	89.83	89.83
Prob (F-statistic)	1.66e-35	1.66e-35
Log-Likelihood	-115.98	-115.98
AIC	240.0	240.0
BIC	252.8	252.8
Coefficient		
Const	5.0173***	6.3066***
	(1.124)	(1.663)
	[0.000]	[0.000]
LN Pop Predicted	-0.1846**	
	(0.088)	
	[0.035]	
LN Pop 'Density' Predicted		-0.4149**
		(0.197)
		[0.035]
LN Real FAI	0.6604***	0.4855***
	(0.076)	(0.139)
	[0.000]	[0.000]
LN College Ratio	0.1615**	0.0087
	(0.053)	(0.058)
	[0.002]	[0.881]
Omnibus	24.159	24.159
Prob(Omnibus)	0.000	0.000
Durbin-Watson	1.687	1.687
Jarque-Bera (JB)	58.699	58.699
Prob(JB)	1.79e-13	1.79e-13
Skew	-0.549	-0.549
Kurtosis	5.548	5.548
Cond. No.	367	465

Note: ***p<0.01, **p<0.05, *p<0.1. Standard Errors are in parentheses. P-values are in brackets. Both models use the 1982 population as an instrument. The IV2SLS models were done manually, where standard errors in the second stage might not be accurately estimated without proper adjustment for the first stage's uncertainty.

capital. Comparing the elasticity of Real FAI to 1996-1997's elasticity in prefecture-level cities between ln(Capital/Employment) and ln(GDP/Employment) of 0.428** (.108) under the 2SLS technique, we can see that the magnitude of capital has increased in China in 13 years (Au & Henderson, 2006). This implies that China has completely moved away from an agricultural economy and is leaving behind the industrial economy, moving towards the service sector. In the same paper, however, their elasticity between ln(Roads per Capita) and ln(GDP/Employment) is statistically insignificant.

Table 8: IV-GMM Models

	Pop as Endog	**Pop 'Density' as Endog**
R-squared	0.6904	0.6106
Adj. R-squared	0.6901	0.6102
F-statistic	4935.2	4647.4
P-value (F-stat)	0.0000	0.0000
No. Observations	2598	2598
R-squared	0.6904	0.6106
Adj. R-squared	0.6901	0.6102
F-statistic	4935.2	4647.4
P-value (F-stat)	0.0000	0.0000
No. Observations	2598	2598
Coefficient		
Const	5.5212*** (0.2700) [0.0000]	5.0804*** (0.2435) [0.0000]
LN Real FAI	0.5439*** (0.0220) [0.0000]	0.6200*** (0.0156) [0.0000]
LN College Ratio	0.0357** (0.0155) [0.0210]	0.1588*** (0.0137) [0.0000]
LN Pop Per Developed Area	-0.2789*** (0.0400) [0.0000]	-
LN Pop	-	-0.1241*** (0.0218) [0.0000]
Endogenous	LN Pop	LN Pop 'Density'
Instruments	LN 1982 Population	LN 1982 Population

Note: ***p<0.01, **p<0.05, *p<0.1. Standard Errors are in parentheses. P-values are in brackets. GMM Covariance, Robust (Heteroskedastic). No available Hansen or Sargan tests due to the limited numbers of instruments.

In my my two-step GMM models, I expanded on the results from Table 7, where now I include the entire panel data in my regression, offering a more robust finding. The observations include only the cities that have corresponding populations from 1982. The coefficients are more statistically significant in this model. Both models agree on the importance of capital density and college ratio. Compared to the previous estimates for capital density, the GMM model further increases the magnitude of capital density's effect on labor productivity. Again, the two endogenous variables both have negative elasticities, with statistical significance.

First-Order Differences

Another method to address the issue of autocorrelation due to the time series data is to test for stationary. As the fixed effects demonstrate, time variables have an effect on the coefficients of my regression. Since my parameters are finite, and parametric approaches assume a stationary stochastic process, I will use the augmented Dickey-Fuller (ADF) test to determine if my variables are stationary.

Table 9: ADF Stationarity Tests for Key Variables across All Cities and Years

Variable	ADF Test	P-Value	Critical Value (1%)	Critical Value (5%)	Test Results
LN Pop	-1.1721	0.6855	-3.4321	-2.8623	non-stationary
LN Labor Prod	-2.1232	0.2353	-3.4321	-2.8623	non-stationary
LN Real FAI	-3.2086	0.0195	-3.4321	-2.8623	stationary
LN Developed Area	-2.9376	0.0411	-3.4321	-2.8623	stationary
LN Pop Per Developed Area	3.5006	1.0000	-3.4321	-2.8623	non-stationary
LN College Ratio	-3.3246	0.0138	-3.4321	-2.8623	stationary
Δ LN Pop	-11.1616	2.78×10^{-20}	-3.4323	-2.8624	Stationary
Δ LN Labor Prod	-6.7872	2.42×10^{-9}	-3.4323	-2.8624	Stationary
Δ LN Real FAI	-7.4614	5.34×10^{-11}	-3.4323	-2.8624	Stationary
Δ LN Developed Area	-8.7638	2.63×10^{-14}	-3.4323	-2.8624	Stationary
Δ LN Pop Per Developed Area	-9.3599	7.87×10^{-16}	-3.4323	-2.8624	Stationary
Δ LN College Ratio	-67.0489	0.00	-3.4323	-2.8624	Stationary

Notes: The number of observations for the original logged variables is 3659, and the number of observations for the first-order differences is 3393. The first-order differences represent the logged versions of population growth rate, real labor productivity growth rate, real capital per labor growth rate, developed areas growth rate, population density growth rate, and college attainment growth rate, respectively, expressed as Δ LN Pop, Δ LN Labor Prod, Δ LN Real FAI, Δ Developed Area, Δ LN College Ratio.

As shown in Table 9, LN population, LN labor productivity, and LN population per developed area are non-stationary. By converting them to their first-order differences, all of the variables become stationary, rejecting the hypothesis of unit root at the critical value of 1%. As a result, I can run regression analyses on the first-order differences of these variables. By converting them to first-order differences, I lose the observations from 2006, explaining the slight shrink in the dataset.

Table 10: Linear Regressions on YoY Differences

	Dependent variable: Δ ln(Real Labor Prod)			
	All Entries	All Entries	Coastal, no 2020	No Outliers, no 2020
Δ ln(College Ratio)	-0.001	-0.000	-0.005	0.012*
	(0.008)	(0.008)	(0.015)	(0.006)
Δ ln(Pop)	-0.095*		-0.078	-0.241
	(0.051)		(0.070)	(0.245)
Δ ln(Pop Per Developed Area)		-0.092***		
		(0.022)		
Δ ln(Real FAI)	0.352***	0.350***	0.304***	0.089***
	(0.047)	(0.047)	(0.081)	(0.011)
Constant	0.032***	0.028***	0.032***	0.063***
	(0.006)	(0.006)	(0.009)	(0.002)
Observations	3423	3423	1299	2482
R^2	0.269	0.271	0.155	0.103
Adjusted R^2	0.268	0.270	0.153	0.102
Residual Std. Error	0.143 (df=3419)	0.143 (df=3419)	0.165 (df=1295)	0.057 (df=2478)
F Statistic	27.230*** (df=3; 3419)	38.510*** (df=3; 3419)	5.528*** (df=3; 1295)	25.486*** (df=3; 2478)

Note: *p<0.1; **p<0.05; ***p<0.01

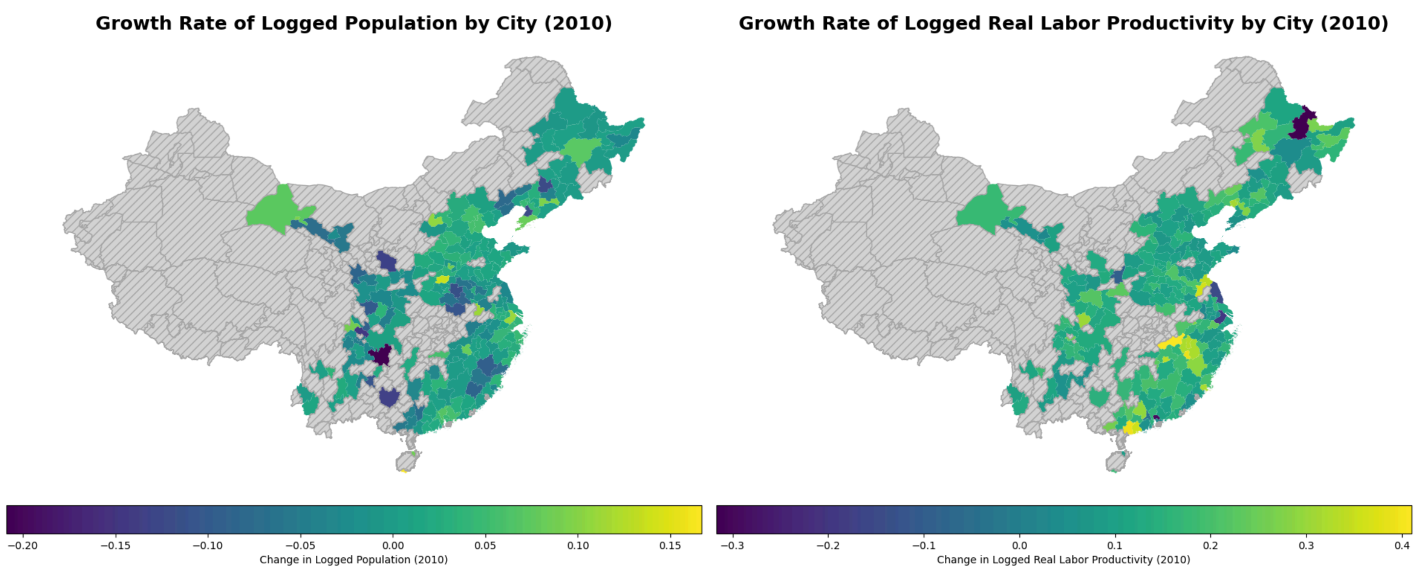
In Table 10, I ran four different regressions. The first two regressions include all entries from the new dataset, separated by the two different agglomeration metrics. The third model includes only coastal provinces. I also decided to take out observations from 2020 due to the increase in GDP and a decrease in employment under COVID-19 conditions. Since the dataset is smaller than before, I decided to treat some of the outliers. The last model excludes all outliers outside of the 25th and 75th percent quantiles for both population growth and labor productivity growth. Overall, although not statistically significant in all except for one model, the coefficient for logged population growth rates appears to be negative. The R-squared values remain small for all four regressions. In the second model, with population density as an explanatory variable, the model finds statistical significance for population per developed area, which is congruent with my findings with the GMM model. The second model implies that a one percent increase in the growth rate of population per developed area will lead to a 0.092 percent decrease in the growth rate of real labor productivity. The capital density remains statistically significant, and the coefficient is positive for all models, also congruent with the GMM model. Due to the lack of statistical significance and explanatory power in these models, I consider using differences lagged two years instead of one.

Table 11: Linear Regressions on Variables with Two Year Differences

	Dependent variable: $\Delta_{t-2}\ln$(Real Labor Prod)			
	All Entries	All Entries	Coastal, no 2020	No Outliers, no 2020
$\Delta_{t-2}\ln$(College Ratio)	-0.001	-0.004	-0.007	0.004
	(0.010)	(0.010)	(0.022)	(0.009)
$\Delta_{t-2}\ln$(Pop)	-0.080		-0.116	0.025
	(0.066)		(0.097)	(0.216)
$\Delta_{t-2}\ln$(Pop Per Developed Area)		-0.136***		
		(0.029)		
$\Delta_{t-2}\ln$(Real FAI)	0.312***	0.305***	0.220***	0.118***
	(0.032)	(0.032)	(0.057)	(0.010)
Constant	0.063***	0.052***	0.069***	0.105***
	(0.008)	(0.008)	(0.015)	(0.004)
Observations	2900	2900	1091	2056
R^2	0.241	0.247	0.099	0.135
Adjusted R^2	0.241	0.247	0.097	0.134
Residual Std. Error	0.192 (df=2896)	0.191 (df=2896)	0.228 (df=1087)	0.093 (df=2052)
F Statistic	37.020*** (df=3; 2896)	54.732*** (df=3; 2896)	5.825*** (df=3; 1087)	43.126*** (df=3; 2052)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11 shows the regression results with two-year lagged differences. The college ratio in the fourth model and the population in the first model lost their statistical significances. The fourth model displays a slightly higher R square, but not enough to be considered. The capital density still remains statistically significant across all models. In search of statistically significant agglomeration effects in the first-differences models, I constructed many regression models, altering the datasets. I chose to use population as the metric for measuring agglomeration in these models because of the possibility that developed areas may be an insufficient method of measuring population density. In Table 12, capital density remains statistically significant with positive coefficients. In the model with the 50 least developed cities in China, measured by the lowest sum of developed areas, the growth rate of the logged population is statistically significant with a negative coefficient. This indicates that, in the least developed cities, an increase of one percent in logged population growth rates in fact decreases the growth rate of logged labor productivity by 0.324 percent. In Table 13, I used the same models to regress overpopulation per developed area instead of just population. Most models see an increase in the R-squared values. Two models also display significance with negative coefficients for population per developed area. Surprisingly, although not statistically significant, the municipalities show a positive coefficient between the logged growth rates of population per developed area and the logged growth rates of labor productivity.



Observe that logged growth rates of population decrease in the middle regions of China, where industrial sectors dominate. Also, observe that logged growth rates of real labor productivity increase near the southeastern coasts, where manufacturing and service sectors dominate. The correlation between the logged growth rates is not visually apparent. Indeed, I can develop more models that isolate the cities based on their characteristics. The low explanatory power of these models hints at the possibility of an omitted variable bias, where the omitted variable correlates to both the growth rate of logged real labor productivity and the growth rate of logged population. Since this paper discusses urban agglomeration effects, an omitted variable that does not account for the agglomeration of people should be left out.

Table 12: More Linear Regressions on YoY Differences

	Dependent variable: Δ ln(Real Labor Prod)								
Variable	Munis	Ind	bot GDP	top GDP	top College	top Pop	top Dev	bot Dev	top Prod
Δ ln(College Ratio)	0.101	0.013	-0.015	0.020	-0.008	0.015	0.012	0.000	0.062*
	(0.290)	(0.017)	(0.021)	(0.036)	(0.034)	(0.033)	(0.036)	(0.016)	(0.037)
Δ ln(Pop)	-0.075	-0.048	-0.164	0.112	-0.013	-0.071	0.011	-0.324***	0.072
	(0.568)	(0.082)	(0.115)	(0.162)	(0.116)	(0.151)	(0.147)	(0.080)	(0.118)
Δ ln(Real FAI)	0.403***	0.239***	0.206***	0.488***	0.580***	0.432***	0.486***	0.251***	0.440***
	(0.084)	(0.014)	(0.021)	(0.032)	(0.031)	(0.035)	(0.035)	(0.018)	(0.019)
Constant	0.028*	0.040***	0.051***	0.017**	0.005	0.022***	0.019**	0.041***	0.024***
	(0.015)	(0.004)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.005)	(0.006)
Observations	52	1875	550	696	693	687	686	616	696
R^2	0.357	0.132	0.150	0.248	0.336	0.184	0.222	0.258	0.441
Adjusted R^2	0.317	0.131	0.145	0.245	0.333	0.180	0.219	0.254	0.438
Residual Std. Error	0.070	0.146	0.138	0.208	0.208	0.199	0.201	0.097	0.122
	(df=48)	(df=1871)	(df=546)	(df=692)	(df=689)	(df=683)	(df=682)	(df=612)	(df=692)
F Statistic	8.880***	95.200***	32.049***	76.000***	116.080***	51.279***	64.960***	70.850***	181.789***
	(df=3; 48)	(df=3; 1871)	(df=3; 546)	(df=3; 692)	(df=3; 689)	(df=3; 683)	(df=3; 682)	(df=3; 612)	(df=3; 692)
Note:	*p<0.1; **p<0.05; ***p<0.01								

Munis are municipalities, the data excludes the year 2020. Ind are the provinces where the industrial and manufacturing sectors account for more than 40 percent of their GDPs. Ind also excludes the year 2020. bot GDP is the 50 cities with the lowest sum of GDPs. top GDP is the 50 cities with the highest sum of GDPs. top College is the 50 cities with the highest sum of college ratios. top Pop is the 50 cities with the highest max of populations. top Dev is the 50 cities with the highest max of developed areas, bot Dev is the 50 cities with the lowest sum of developed areas, and top Prod is the 50 cities with the highest sum of growth in labor productivity.

Table 13: More Linear Regressions on YoY Differences

	Dependent variable: Δ ln(Real Labor Prod)								
Variable	Munis	Ind	bot GDP	top GDP	top College	top Pop	top Dev	bot Dev	top Prod
Δ ln(College Ratio)	0.221	0.012	-0.012	0.030	-0.007	0.019	0.016	0.010	0.048
	(0.280)	(0.017)	(0.021)	(0.035)	(0.034)	(0.033)	(0.036)	(0.015)	(0.037)
Δ ln(Pop Per Developed Area)	0.162	-0.142***	-0.090*	-0.100	-0.104	-0.136	-0.080	-0.123***	-0.056
	(0.191)	(0.039)	(0.052)	(0.094)	(0.078)	(0.090)	(0.090)	(0.042)	(0.060)
Δ ln(Real FAI)	0.407***	0.236***	0.203***	0.488***	0.576***	0.428***	0.482***	0.248***	0.439***
	(0.082)	(0.014)	(0.021)	(0.032)	(0.031)	(0.035)	(0.035)	(0.018)	(0.019)
Constant	0.029**	0.034***	0.048***	0.016*	0.003	0.016*	0.017*	0.037***	0.024***
	(0.012)	(0.004)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)
Observations	52	1875	550	696	693	687	686	616	696
R^2	0.366	0.138	0.151	0.249	0.337	0.186	0.223	0.249	0.441
Adjusted R^2	0.327	0.137	0.147	0.245	0.335	0.183	0.220	0.245	0.439
Residual Std. Error	0.069	0.145	0.138	0.207	0.208	0.199	0.201	0.098	0.122
	(df=48)	(df=1871)	(df=546)	(df=692)	(df=689)	(df=683)	(df=682)	(df=612)	(df=692)
F Statistic	9.245***	100.187***	32.422***	76.296***	116.957***	52.132***	65.291***	67.470***	182.089***
	(df=3; 48)	(df=3; 1871)	(df=3; 546)	(df=3; 692)	(df=3; 689)	(df=3; 683)	(df=3; 682)	(df=3; 612)	(df=3; 692)
Note:	*p<0.1; **p<0.05; ***p<0.01								

Munis are municipalities, the data excludes the year 2020. Ind are the provinces where the industrial and manufacturing sectors account for more than 40 percent of their GDPs. Ind also excludes the year 2020. bot GDP is the 50 cities with the lowest sum of GDPs. top GDP is the 50 cities with the highest sum of GDPs. top College is the 50 cities with the highest sum of college ratios. top Pop is the 50 cities with the highest max of populations. top Dev is the 50 cities with the highest max of developed areas, bot Dev is the 50 cities with the lowest sum of developed areas, and top Prod is the 50 cities with the highest sum of growth in labor productivity.

Future Research

In analyzing the effects of agglomeration in China, there are indeed better metrics than those for population and developed areas. Since population can be highly correlated with GDP or human capital, one can use other means to measure agglomeration (Glaeser & Resseger, 2010). Some economists have even used satellite imagery to measure agglomeration and urban activity (Liu & Chen, 2017). Moreover, the impact of educational attainment, as quantified through the college ratio, on China's economic productivity warrants further examination. With the evolving workforce dynamics, as a greater segment of the population achieves tertiary education, the implications for human capital on productivity could potentially shift.

Since I studied China's agglomeration effects on a macro level, I believe that smaller case studies may yield more resounding conclusions. With a more specific case study, one can even derive an urban agglomeration index that accounts for the proximity of people rather than political borders, an agglomeration index that passes Lemelin et al.'s criterion. As China was prosperous in lifting hundreds of millions out of poverty, there are methods for other developing countries to achieve the same. However, to better understand the effects of China's massive project in urbanizing hundreds of cities and causing a huge migration, we must conduct more studies with innovative ideas such as satellite imaging or meta-analyses.

Conclusion

This paper presents the regression analysis on 262 prefecture-level cities in China, primarily using domestic data to evaluate China's urban livelihood during rapid economic success. As the large population hubs slowly cement and population growth slows down, China must balance its priorities between the urban and rural cities.

Using FE, RE, 2SLS, two-step GMM, and first-order differences, I conducted regressions on real labor productivity in 2005 Yuan with two separate urban agglomeration metrics: reported population in the legislative area and the quotient between the reported population and the registered urban built-up areas. Through my analysis, I hoped to find a positive correlation between my agglomeration metrics and real labor productivity, as many economists have in developed economies. By establishing the relationships between the agglomeration metrics and real labor productivity, my paper reveals the following:

1. In the majority of prefecture-level cities, there is a negative relationship between population and real labor productivity; a negative relationship between the growth rate of population and the growth rate of real labor productivity
2. a slightly stronger negative relationship between the quotient of population over urban built-up areas and real labor productivity, and a negative relationship between the growth rate of population over urban built-up areas and the growth rate of real labor productivity.
3. There may be omitted variables that influence both the growth rates of labor productivity and the growth rate of the population.

As China experiences negative urban agglomeration effects as a whole, then this means one of two theories: (1) A majority of Chinese cities have reached the spatial equilibrium where the increase of population increases the congestion costs more than labor productivity, or public infrastructures cannot match the influx of migrants. (2) There exists a threshold where developing countries, even with theoretically developed cities, must overcome a cultural or educational barrier in order to become more productive together. As a policy implication, China's Hukou system and developing preferential cities put a barrier to organic city growth. Instead of limiting the effective population to increase the efficiency of metropolitan travel, Chinese cities experience congestion effects nonetheless, leading to a decrease in real labor productivity as the population increases. As the spatial equilibrium persists to occur, the lack of labor mobility will always lead to inefficiencies in urban agglomeration.

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[5] Link to my Google Colab Notebook.

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