Urban Intensity in Theory and Practice: Empirical Determining Mechanism of Floor Area Ratio and Its Deviation from the Classic Location Theories in Beijing

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Abstract: Background: Classic locational principles predict a picture of urban intensity decaying from the city center to the periphery under ideal assumptions. However, various exogenous factors can influence the real-world urban intensity and often deviate from the theoretical pattern. The specific mechanisms are worthy of exploration and are of potential theoretical and practical significance. Methods: In this paper, we consider two city districts with typical urban locations, namely, Changping and Chaoyang in Beijing, and construct mechanistic models of the status quo urban intensity (floor area ratio, \( \text{FAR} \)) utilizing multisource spatiotemporal big data. We further compare these models with the “theoretically ideal” \( \text{FAR} \) patterns as would be predicted by applied locational theories. Results: We find that the status quo \( \text{FAR} \) distribution generally conforms to the theoretical predictions but still exhibits regional deviations that can be explained by historical inertia and influence from particular policies. Conclusion: We conclude this paper with discussions on the findings’ methodological and practical implications for urban planning institutions, especially in a transition economy context.

Keywords: urban intensity; floor area ratio (\( \text{FAR} \)); locational theory; spatiotemporal big data; Beijing

1. Introduction

As predicted by Northam’s famous urbanization curve [1], China, with the country’s urbanization level approaching 65% by 2021, is undergoing a historical transition from rapid urban population expansion to a new phase featuring the slowing of the urbanization rate. In particular, mega-cities such as Beijing and Shanghai have effectively shifted to an urban development goal of “stock optimization”, which means that the emphasis of urban development and planning is placed on the spatial optimization of existing urban areas. Undoubtedly, this new policy orientation has highlighted the need for a stronger scientific basis of urban spatial planning that would guide the abovementioned optimization [2].

The spatial distribution of urban intensity is one of the most important issues considered in urban planning [3]. Intuitively, the skyline heights in most cities show a decreasing trend from the city center to the periphery [4], which is usually explained as an effect of the agglomeration economy in a market economy [5]. Admittedly, classic location theories allow for local deviations in the distribution of urban intensity from the perfect bid rent curve due to geographic heterogeneity, traffic congestion, and other reasons. However, there are still many cities where the distribution pattern of urban intensity deviates significantly from the reasonable degree allowed by these theories. Beijing is a typical example of a city of this kind (Figure 1). This seemingly unusual pattern poses a potential challenge to urban intensity theories that are based on economic rationality.
Previous studies have offered some explanations for the above question. First, during the centrally planned economy years (1952–1992), Beijing experienced drastic urban expansion. Thus, the urban planning rooted in the planned economy system during this period left a deep mark on the urban intensity picture of the city. Next, since the transition to a market economy in 1992, and especially since the introduction of the free housing market in 1998, Beijing has undergone three rounds of urban master plans under the general principles of the market economy. However, they were also developed in the context of various policy orientations. Therefore, understanding its formation mechanisms would be a valuable contribution to applied economic geographical location theories, especially in the context of transitional economies. Nevertheless, despite the above explanations, they are generally qualitative in nature and are thus inadequate in directly supporting urban planning practices.

The presented paper aims to bridge the knowledge gap by quantitatively investigating the formulation mechanisms of Beijing’s urban intensity. In the rest of this paper, we first present a critical literature review of the relevant theories on urban intensity. Next, utilizing the floor area ratio (FAR), i.e., the ratio of the total floor area of buildings in a certain plot of land to the area of the plot as an indicator of urban intensity [8], we take two jurisdictional districts in Beijing as cases and develop empirical models of the spatial distribution mechanism of their status quo FAR under the guidance of classic economic geographical location theories. Meanwhile, based on applied economic geographical location theories, we construct three scenarios of “ideal” FAR distribution. Then, by comparing the two, we identify the areas with significant status quo deviations from the “ideal” pattern scenarios and analyze the reasons for such deviations. We hope to answer the main research question of “what are the specific factors influencing the city’s intensity distribution, and by what mechanisms do they work to shape the seemingly erratic

Figure 1. Study area.
status quo urban intensity patterns?”. Our hypotheses, deduced from the above qualitative explanations, that complex factors including historical path dependency, policy orientations, and socioeconomic heterogeneity together shape the city’s intensity patterns will be tested with the above analyses. We conclude the paper by discussing the methodological and practical implications of the findings for the planning institution.

This research would previously have involved intensive empirical work, traditionally limited by data availability. Fortunately, with the recent development of digital urban planning support systems and information technology in general, there is an increasing wealth of big data collected by pervasive Internet- and Internet of Things (IoT)-based devices [9]. Available data sources include points of interest (POI) [10–12], land price [13], traffic [14], etc., which provide strong support for this research.

2. Literature Review

Under free market assumptions, classic economic geographical location theories posit that the public and private sectors combined determine urban land use patterns mainly through the effects of the economy of scale [15]. Specific theories in this field include bid rent theory [16] and land rent theory [5]. These theories explain the relationship between land rent, locational choice, and land use in monocentric cities. Subsequent theoretical developments in this field further consider traffic congestion [17] and polycentricity [18] and find that these factors change the skyline curvature under the equilibrium rent gradient [19]. Spatial anisotropy issues are also taken into account. For instance, Clark constructed a uniform exponential function to represent the relationship between land use intensity and the distance from the city center [20]. In short, the above theories give a picture of the intensity of urban land use, with the building floor area ratio (FAR) being an indicator, decaying in a gradient from the city center to the periphery, and the distance–decay pattern, although usually anisotropic, still forms a multilayer structure. Houston can be considered a typical illustration of the theoretical prediction, which, in the absence of zoning interventions, exhibits a representative landscape of monocentric decay of urban intensity in a market economy [21].

However, many cities in the real world demonstrate a high degree of diversity in urban intensity distribution, which does not always resemble the perfect, or even adjusted, bid rent pattern. The reasons for this are manifold. First, in nonmarket economies, urban intensity certainly does not obey the diktats of economic geography locational rules. In such economies, cities’ location, function, size, and growth are largely “manipulated” by the state [22]. Moscow in the 20th century is an example of this type of centrally planned city [4,23].

Second, even in a market economy, urban intensity is still influenced by historical, environmental, and policy factors [24,25]. Among these factors, urban planning intervention plays a significant role [26,27]. Beyond the pure economic geography pursuits for locational value maximization, planners tend to consider the issue of urban intensity from a broader public interest perspective. It is often argued that reliance on free market mechanisms may turn land development into a growth machine dictated solely by profit motives but at broad social, resource, and environmental costs [28]. Therefore, policy interventions are necessary to correct externalities by mitigating market failures and providing public goods [29]. A typical example of systematic planning interventions in urban land use is the zoning system in the US, which explicitly restricts urban intensity (along with other land use features) by setting FAR targets [30]. As mentioned earlier, the considerations in setting such restrictions are diverse. For example, these may include ensuring access to public services [31], preventing urban sprawl [32], and properly matching occupational and residential urban functions [33]. Similar systems are prevalent worldwide, such as China’s regulatory planning system [34]. In addition, various types of ad hoc policy interventions also influence urban intensity. For example, the US institution of the Transfer of Development Rights allows for transferring FAR quotas among urban plots, which applies
especially in open spaces, historic buildings, and natural and agricultural conservation areas [35].

All of these factors render the formulation mechanism of urban intensity in the real world often different from the logic of economic geography location theories. Putting this another way, if the latter gives a theoretical counterpoint, deviations in the former reflect the role of various geographical and policy factors, especially urban planning policies. Thus, exploring the difference between a city’s status quo and the “theoretically ideal” intensity distribution helps to answer the question of “why does the intensity distribution of the city deviate from the theoretical predictions”, which would shed light on urban geography theories. In practical terms, it will also help us to understand the logic and effects of urban planning, diagnose the problems in the status quo, and inspire future urban planning policies in terms of the rational planning of urban intensity [34,36,37].

3. Methodology

3.1. Study Area

This paper took two districts in Beijing, namely, Changping and Chaoyang, as the study area. The choice of the study area considered certain peculiarities in Beijing. We deliberately avoided the “old city”, namely, the Dongcheng and Xicheng Districts. Although they assume a geographically central location in the city, they do not follow location theory because they have strict development restrictions for historic preservation purposes, and thus, it is obviously inappropriate to try to explain their urban intensity distribution within a location theory framework. Furthermore, considering that agricultural land and ecological protection land do not undergo urban development, we excluded the areas outside the urban development boundary as stipulated in the Measures for the Management of Ecological Control Line and Urban Development Boundary in Beijing. This left us with the developed parts of Chaoyang and Changping Districts, representing the core, mature urban areas, and the still urbanizing areas of Beijing, respectively. According to the Zoning Ordinance of Chaoyang and Changping (2017–2035), the urban areas in the former were divided into six superzones and four in the latter (Figure 1).

3.2. Empirical Modeling of the Formulation Mechanism of Urban Intensity

Based on a basic unit of analysis of a 250 × 250 m regular grid, we constructed empirical models of the urban intensity formulation mechanism. The models took the gridded FAR as the dependent variable. The independent variables were chosen by considering the various urban intensity-influencing factors mentioned in the introduction, including housing price, land use, public services, and transportation. Based on economic geography location theories, land value directly represents urban intensity [38]. We use the price data of second-hand housing transactions as a proxy. The structure of land use also directly predicts the bid rent curve [39]. We assigned a value to this variable by counting the number of public service POI categories in each analysis grid. The level of public service provision is closely related to urban intensity [40]. We chose the business, shopping, financial, medical, parking, primary education, and entertainment POIs as variables representing instantaneous population intensity. We assigned values to each variable by counting the number of POIs of the corresponding type in each analysis grid. Traffic was reflected in regional road capacity and was considered to set the upper limit of urban intensity [41]. We chose bus stations, subway stations, national roads, provincial roads (expressways), county-level roads (main roads), and township-level roads (neighborhood roads) as variables and assigned values to each variable by counting the number of bus stations, the number of 250 m radial circles of subway stations, and the length of roads in each analysis grid. A description of the variables and their expected signs are shown in Table 1.
Table 1. Variable structure.

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Expected Sign</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public services (POI proximity)</td>
<td>Business</td>
<td>+</td>
<td>[42]</td>
</tr>
<tr>
<td></td>
<td>Shopping</td>
<td>+</td>
<td>[43]</td>
</tr>
<tr>
<td></td>
<td>Finance</td>
<td>+</td>
<td>[12]</td>
</tr>
<tr>
<td></td>
<td>Medical</td>
<td>?</td>
<td>[44]</td>
</tr>
<tr>
<td></td>
<td>Parking</td>
<td>?</td>
<td>[45]</td>
</tr>
<tr>
<td></td>
<td>Primary education</td>
<td>+</td>
<td>[46]</td>
</tr>
<tr>
<td></td>
<td>Entertainment</td>
<td>−</td>
<td>[47]</td>
</tr>
<tr>
<td>Transportation (POI proximity)</td>
<td>Public transport stations</td>
<td>+</td>
<td>[48,49]</td>
</tr>
<tr>
<td></td>
<td>Subway stations</td>
<td>+</td>
<td>[50,51]</td>
</tr>
<tr>
<td></td>
<td>National roads, provincial</td>
<td>?</td>
<td>[52]</td>
</tr>
<tr>
<td></td>
<td>roads, county-level roads</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Township-level Roads</td>
<td>+</td>
<td>[38]</td>
</tr>
<tr>
<td>Land value</td>
<td>Second-hand housing transaction price</td>
<td>+</td>
<td>[36,53]</td>
</tr>
<tr>
<td>Land use structure</td>
<td>Land use mixture (number of public service types)</td>
<td>+</td>
<td>[38,54]</td>
</tr>
</tbody>
</table>

* + and − represent the increasing and decreasing effects on urban density, respectively, and ? denotes the a priori to-be-determined sign.

Without loss of generality, we use generalized linear regression to construct the models and the ordinary least squares (OLS) method for parameter estimation. Due to the potential correlation between some variables, we performed a multicollinearity diagnosis on the regression results.

Additionally, for comparison, we constructed three nonlinear machine learning models: XGBoost, random forest, and gradient boosting regression, with the same variable structure. We performed stepwise regression to achieve the best fit. We chose the model with the best explanatory power by comparing the R2 values of the four types of models.

In terms of the spatial scope, four different models were constructed for four regions, including Chaoyang District, Changping District, the central areas of Chaoyang, and Changping New Town, to understand the differences in urban intensity formulation mechanisms in city regions with different locations.

3.3. “Ideal” Urban Intensity Modeling

Meanwhile, based on applied economic geographical theories, we constructed models to set up scenarios of urban intensity distribution that are “theoretically ideal”. As a starting point, under the “featureless plain” assumption, population density could be used as a direct proxy for the FAR. Next, we loosened the homogeneity assumption and considered the factors that would “distort” the concentric circle-shaped intensity distribution. First, considering that the supply of public services is an essential element limiting the number of residents in a city, we introduced this indicator to correct the relationship between population density and FAR. Second, to simulate the distance-decaying service capacity of public services, we used the minimum cumulative resistance (MCR) [55] approach to introduce spatial resistance in public service provision. We took six types of public service POI, including business, shopping, finance, medical, primary education, and parking, as the source in the MCR model and set the resistance with the inverse of the average road travel speed and the walkable buffer zone of the subway stations (Figure 2).
Finally, considering that different urban functions and planning orientations will affect the distribution of urban intensity, we outputted three scenarios of urban intensity distribution with different weighing schemes, where the specific weights for the importance of relevant POI as sources as well as traffic accessibility as resistance were obtained through expert scoring (The specific weights were determined through five rounds of expert consultation with a total of eight experienced urban planners from the College of Architecture and Landscape Architecture at Peking University, the College of Urban and Environmental Sciences at Peking University, and the Beijing Municipal Institute of City Planning). The three scenarios represent the planning orientations of the maximum value-added land use, balanced land use, and enhanced transit-oriented land use, respectively (Table 2).

Overall, the following equation provides the “theoretically ideal” urban intensity (FAR):

\[
\text{FAR} = \frac{A + M}{\sum A + M} \times TA
\]

where \( A \) denotes the plot area, \( M \) is the average value of the public service of the plot, and \( TA \) is the total area size of the buildings in the plot.

To compare the difference between the “ideal” FAR and the status quo, we superimposed the two to obtain a different surface. By comparing the different surfaces of the three schemes, the scenario with the slightest standard deviation of the different surfaces was chosen as the final result of the “ideal” urban intensity. We also calculated subregional means for the “ideal” urban intensity surface according to the zoning plan’s area division.

Figure 2. “Ideal” urban intensity scenario setting under applied location theory guidelines.
Table 2. POI weighting in the three planning scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Weighing Type</th>
<th>Weighing Item</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Resistance (accessibility weights)</td>
<td>Road accessibility; transit station accessibility</td>
<td>1:1</td>
</tr>
<tr>
<td>Balanced land use</td>
<td>Source</td>
<td>Business: shopping; finance, medical; primary education; parking</td>
<td>1/6:1/6:1/6:1/6:1/6:1/6</td>
</tr>
<tr>
<td></td>
<td>Resistance</td>
<td>Road accessibility; transit station accessibility</td>
<td>1:1</td>
</tr>
<tr>
<td></td>
<td>Resistance</td>
<td>Road accessibility; transit station accessibility</td>
<td>1:2</td>
</tr>
</tbody>
</table>

3.4. Data

The data used in the study included the area’s public service facilities, housing prices, and status quo urban intensity (FAR) (Table 3). Among them, for the bus and subway stations, we accessed the API of the Gaode Map data development platform (https://lbs.amap.com, accessed on 1 January 2017) and geocoded the obtained data for mapping; for the housing price data, we first obtained them through web crawlers, carried out data cleaning by removing duplicate and abnormal values, and then performed kriging spatial interpolation (the semivariance function is an ordinary spherical function with search radius points = 12 and maximum distance = diagonal length of the range) to obtain a continuous surface.

Table 3. Data sources.

<table>
<thead>
<tr>
<th>Category</th>
<th>Data</th>
<th>Contents</th>
<th>Source</th>
<th>Spatial/Temporal Resolution</th>
<th>Acquisition Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public service</td>
<td>Bus stations, subway stations</td>
<td>/</td>
<td>Gaode Map data development platform (<a href="https://lbs.amap.com">https://lbs.amap.com</a>, accessed on 1 January 2017)</td>
<td>10 m/1a</td>
<td>January 2017</td>
</tr>
<tr>
<td></td>
<td>National highways, provincial roads, county roads, township roads</td>
<td>/</td>
<td>Beijing Municipal Transportation Commission (<a href="http://jtw.beijing.gov.cn">http://jtw.beijing.gov.cn</a>, accessed on 1 January 2017)</td>
<td>10 m/1a</td>
<td>January 2017</td>
</tr>
<tr>
<td></td>
<td>Mansions</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Shopping</td>
<td>Shopping center, supermarket, wholesale city, home appliance city, department store building</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Finance</td>
<td>Banks</td>
<td>2016 Baidu Map POI Data</td>
<td>10 m/0.5-2a</td>
<td>December 2016</td>
</tr>
<tr>
<td></td>
<td>Entertainment</td>
<td>Cinemas, KTV, entertainment clubs, theaters, stadiums</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hospital</td>
<td>Health centers, hospitals</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Parking</td>
<td>Parking</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Primary Education</td>
<td>Primary and secondary schools</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Housing price</td>
<td>Second-hand housing transaction price</td>
<td>/</td>
<td>2018 Fengtiansia second-hand house price website (<a href="https://www.sofang.com">https://www.sofang.com</a>, accessed on 1 December 2018)</td>
<td>10 m/1a</td>
<td>December 2018</td>
</tr>
<tr>
<td>Urban intensity</td>
<td>FAR</td>
<td>/</td>
<td>Building-level data from the 2016 Geographic State Survey and land parcel data from the Landuse Change Survey</td>
<td>30 m/1-5a</td>
<td>December 2016</td>
</tr>
</tbody>
</table>
4. Results

4.1. Empirical Models

For the entire study area, the goodness-of-fit of the four fitting methods is shown in Table 4. There is no significant difference between the linear regression and machine learning models. Nevertheless, the former helps us to better understand the independent variables’ contribution structure. Therefore, we choose multiple linear regression to model the four subareas as stipulated earlier. The results are shown in Table 5.

Table 4. Goodness-of-fit of the four model fitting methods.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Linear Regression</th>
<th>XGBoost</th>
<th>Random Forest</th>
<th>Gradient Boosting Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R²</td>
<td>0.454</td>
<td>0.223</td>
<td>0.415</td>
</tr>
</tbody>
</table>

Table 5. Regression results of status quo FAR.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Chaoyang District</th>
<th>Changping District</th>
<th>Chaoyang Central District</th>
<th>Changping New Town</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B (SE.) Beta</td>
<td>VIF</td>
<td>B (SE.) Beta</td>
<td>VIF</td>
</tr>
<tr>
<td>Business</td>
<td>0.082 *** (0.014)</td>
<td>0.080 1.610</td>
<td>0.008 (0.040)</td>
<td>0.004 1.201</td>
</tr>
<tr>
<td>Shopping</td>
<td>0.080 *** (0.012)</td>
<td>0.086 1.385</td>
<td>0.010 (0.077)</td>
<td>0.106 1.372</td>
</tr>
<tr>
<td>Finance</td>
<td>0.053 *** (0.009)</td>
<td>0.090 1.954</td>
<td>0.008 (0.008)</td>
<td>0.009 1.694</td>
</tr>
<tr>
<td>Entertainment</td>
<td>−0.054 *** (−0.025)</td>
<td>−0.025 1.099</td>
<td>−0.020 (−0.050)</td>
<td>−0.023 1.207</td>
</tr>
<tr>
<td>Medical</td>
<td>−0.014 (0.017)</td>
<td>−0.009 1.022</td>
<td>0.026 (0.016)</td>
<td>0.019 1.031</td>
</tr>
<tr>
<td>Parking</td>
<td>0.156 *** (0.016)</td>
<td>0.154 2.076</td>
<td>−0.029 (0.026)</td>
<td>−0.016 1.580</td>
</tr>
<tr>
<td>Primary education</td>
<td>0.034 (0.039)</td>
<td>0.010 1.093</td>
<td>−0.043 (0.040)</td>
<td>−0.013 1.092</td>
</tr>
<tr>
<td>Bus stations</td>
<td>3.05 × 10⁻⁴ (1.23 × 10⁻⁴)</td>
<td>0.027 1.004</td>
<td>0.002 (0.001)</td>
<td>0.026 1.012</td>
</tr>
<tr>
<td>Subway stations</td>
<td>0.111 *** (0.026)</td>
<td>0.047 1.062</td>
<td>0.219 (0.028)</td>
<td>0.093 1.046</td>
</tr>
<tr>
<td>National, provincial, and county-level roads</td>
<td>−0.048 *** (−0.010)</td>
<td>−0.050 1.013</td>
<td>−0.015 (−0.004)</td>
<td>−0.051 1.031</td>
</tr>
<tr>
<td>Township-level roads</td>
<td>0.019 *** (0.003)</td>
<td>0.072 1.162</td>
<td>0.014 (0.002)</td>
<td>0.083 1.114</td>
</tr>
<tr>
<td>Ln (house price)</td>
<td>0.367 *** (0.057)</td>
<td>0.075 1.124</td>
<td>0.594 (0.032)</td>
<td>0.226 1.099</td>
</tr>
<tr>
<td>Land use mixture</td>
<td>0.191 *** (0.013)</td>
<td>0.298 3.232</td>
<td>0.210 (0.013)</td>
<td>0.336 3.005</td>
</tr>
</tbody>
</table>

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1; robust errors in parentheses.

The results show that most independent variables positively contribute to urban intensity. Comparing Chaoyang and Changping, the former’s urban intensity bears a significant relationship with each explanatory factor, and the extent of influence from public services exceeds that of transportation factors. In contrast, in Changping, the influence of transportation (bus stations and subway stations) and cost (house price and land use mixture) factors on urban intensity is more prominent. The difference may be because Chaoyang, Beijing’s city center with mature urban development and critical urban functions, reflects the proxy role of public service facilities for urban intensity, while Changping is a new urban subcenter still under development, thus highlighting the forerunner role of the transportation system in urban development.

Regarding the contribution of the public service variables, factors related to shopping are found to impact urban intensity prominently. The same applies to the parking variable, an essential service for daily life. In contrast, the primary education and medical care variables show a weaker impact on urban intensity, possibly due to the high coverage of these two types of services as dictated by urban planning requirements. In addition, the presence of entertainment facilities causes the area to attract many people during service times, generating a higher instantaneous population density and higher urban intensity.
In terms of transportation services, public transportation, represented by bus and subway stations, contributes positively to urban intensity. In both Chaoyang and Changping, the presence of subway stations significantly and positively affects the FAR of the surrounding area. Regarding roads, the correlation between high-level roads and urban intensity is negative, while those of the lower-level roads are positive. This distinction may be because high-level roads emphasize large-scale transportation functions per se and thus tend to avoid high-intensity urban areas. In contrast, the lower-level roads are more related to residential and living services, which can withstand higher urban intensity.

The regression coefficient between housing prices and urban intensity is positive, which may be explained by the trade-off between FAR and commuting/public service provision costs in classic location theories [31,33]. The positive correlation seems to imply that in the study area, the benefits of higher FAR in places with high housing prices are higher than the costs of increased provision of public services and commuting.

Finally, the positive contribution of land use structure to urban intensity is found to be substantial. This contribution may be because mixed-functional plots can satisfy multiple living needs while reducing the time and screening costs for accessing services, thus contributing to high urban intensity.

Moreover, comparing the regression results for Chaoyang Central District and Changping New Town, which represent a mature central city area and an emerging edge city, we find significant differences in the role of the business, financial, and parking variables. In Chaoyang Central District, the factors exhibit significant and positive effects on urban intensity, while in Changping New Town, the effects are insignificant. In contrast, the impact of land use mixture on the latter’s urban intensity is more prominent than that of the former. Based on the abovementioned cost/benefit trade-off, the findings may imply that reducing the time cost of access to services is more critical in shaping urban intensity for urban areas still in the early stages of development. However, the subway station variable is insignificant in both subareas. This finding may imply that although the presence or absence of subway stations significantly affects the urban intensity at the citywide scale, the correlation is compelling more through the large-scale contrast between urban centers and suburbs rather than in mesoscale and microscale structures. For example, the high density of subway stations in already dense urban centers may prevent them from significantly affecting urban intensity.

4.2. “Ideal” Models

The FAR results based on the three superposition methods are shown in Figure 3. There is no significant difference in the overall distribution of FAR in the three scenarios. This finding indicates that the theoretically ideal FAR is not very sensitive to changes in the weights of shopping and rail transportation, and the direction of the contribution of public services and transportation to it is consistent.

The “ideal” FAR patterns in Chaoyang and Changping are significantly different. The former is generally higher than the latter overall. High FAR occurs in the central city area of Chaoyang, Beiyuan, Jiuxianqiao, and Dingfuzhuang, showing a finger-shaped radiation structure from the center to the periphery, which is highly consistent with the distribution of the arterial transportation system. Nevertheless, in Changping, a high FAR appears in the old town area and Changping New Town, Tiantongyuan, and the northern area of Future Science City, with a more fragmented pattern and an apparent polycentric structure. This may result from the strict ecological protection policies imposed on the district that separate the scattered urbanized areas from the background of ecological conservation areas.
4.3. Comparison between the “Ideal” and Empirical Models

Overlaying the three “ideal” urban intensity scenarios with the status quo FAR distribution, the results are shown in Figure 4. Scenario 1, the maximum land use value-added scenario, has the smallest standard deviation among the three scenarios. Based on the scenario, shopping-related factors exhibit a higher contribution to urban intensity in the “ideal” model than in reality. In contrast, high-level roads, such as national, provincial, and county roads, positively contribute to urban intensity in the “ideal” model, probably because of their perceived role in enhancing the accessibility of public services. However, these variables negatively contribute to urban intensity in the empirical models. This finding indicates that the transit-oriented development strategy, although highly advocated for by the urban planning bureau [56,57], has not already shown prominent effects in reality.

Figure 3. “Theoretically ideal” FAR distribution in the three scenarios.

Figure 4. Difference between the theoretical ideal FAR and the status quo FAR in the three scenarios.

Summarizing the “ideal”/empirical differences for neighborhood unit means (compilation units of Regulatory Plan) (Figure 5), it can be seen that the status quo FAR is higher than the theoretically ideal value in the Tiantongyuan area in Changping, the central city area in Chaoyang, and the Beiyuan area, all located along the periphery of Beijing’s city.
proper. The opposite is true for Changping New Town, an independent suburban edge city. The status quo FAR is close to the “ideal” projections in other areas. We will elaborate on the implications of the above findings in the Discussion section.

![Legend](FAR.png)

**Figure 5.** Grivation results of Scenario 1.

5. Discussion

This paper empirically investigates the formulation mechanism of urban intensity in Beijing and compares the status quo with the projection of a theoretically ideal FAR model. This work attempts to guide urban planning with quantitative theoretical and empirical analysis that endorse scientific rationality, echoing a long-established academic tradition in urban planning [58]. In particular, in terms of the planning for urban intensity, many attempts have been made to use geographic spatial analysis in the service of urban and regional science centered on location theory, such as applying linear regression analysis and urban growth models [59], the use of logistic regression to explain the importance of urban growth drivers [60], and the application of spatial econometrics to environmental and resource studies and planning [61]. In China, however, although urban planning has been primarily experience-based, quantitative methods have been gradually introduced in recent years, and attempts have been made to achieve rational planning [62]. To a large extent, one of the focuses of such attempts lies on the issue of urban intensity, as it is directly linked to “land finance” and is thus of particular importance in municipal governance [63]. Therefore, with cities in China generally initiating a new round of regulatory planning, rational designation of urban intensity in planning is necessary and urgent. We hope to present a deeper understanding of the formulation mechanism of urban intensity through Beijing’s case study to contribute to this ongoing endeavor from a rational perspective.

5.1. The Determinants of Urban Intensity in Beijing

Our findings show that the urban intensity in Beijing, in mechanistic terms, is generally consistent with the predictions of classic locational theories in economic geography. On the one hand, urban intensity tends to be high in areas rich in business and shopping services. On the other hand, under the trade-off of land rent and travel costs, the economic cost of land and the time cost of travel jointly determine the distribution of urban intensity, resulting in a highly concentrated urban land development pattern.

In contrast, public service facilities such as medical care and primary education do not significantly impact urban intensity. The reason for this may be two-fold. First, although such facilities have some population-attracting capacity, their own FAR tends to be very low. Second, Chinese urban planning traditionally lays out all kinds of public service facilities in a relatively homogeneous manner throughout the city as dictated by the “thousand-population quota” (the provisioned volume of various public service facilities per 1000 residents), resulting in an even spatial distribution of these facilities in the city, and thus, they appear less sensitive to urban intensity.

The impact of transportation infrastructure on urban intensity is polarized. On the one hand, low-level roads (township-level roads) and rail stations positively contribute to
urban intensity. On the other hand, urban intensity is lower near high-level roads such as national, provincial, and county-level roads. Traditionally, deeply influenced by the idea of functional zoning in the Athens Charter [64], Chinese urban planners tend to place high-level transportation systems in separate and open urban spaces. Although transit-oriented development (TOD) has emerged and been advocated for in recent years, emphasizing the use of transportation infrastructure to guide urban development, its implementation needs time, as is evident in the results. Therefore, the traditional model’s profound path dependency explains the negative correlation between the current urban intensity status and high-level roads.

Regarding subregional comparisons within cities, subregions differ in the relevance of various factors influencing urban intensity due to their different levels of maturity of urban development in economic and population terms. Factors related to business and shopping and living services and facilities, such as shopping, finance, and parking, significantly and positively impact the intensity of mature city centers. In contrast, the intensity of new urban areas under development is influenced more by travel time costs, reflecting a substantial reliance on transportation infrastructures such as amenity (lower-level) roads and bus stops.

5.2. Deviation of the Urban Intensity from the Classic Location Theory: An Explanation

Although generally consistent in spatial patterns, we find that the status quo urban intensity in the study area shows specific structural deviations from the predictions of the “ideal” models in the scenario analysis, manifesting itself differently in different parts of the urban area. The reasons for this may include the historical inertia of the urban structure, cultural heritage, environmental protection requirements, and specific policy guidance.

First, historical factors play a prominent role [65]. As a city with a history of at least eight hundred years on its present site and as the national capital for most of that time, Beijing’s current urban intensity pattern carries a great deal of historical inertia. In particular, during its first period of rapid development as a modern city (1949–1978), urban intensity planning under the planned economy system did not operate according to the ideal market economy model. In contrast, urban planning in the planned economy imposed a strict ratio of various types of land use at the neighborhood scale, which resulted in an almost even distribution of intensity throughout the city. Such reasons led to a largely homogeneous distribution of FAR, meaning that the city’s skyline did not show a decay pattern from the center to the periphery. This pattern is typical in cities of countries with a long-standing planned economy system [1]. It also applies in Beijing, manifesting itself in many parts of the city space that do not appear to show an otherwise “rational” intensity pattern according to market economy principles.

Second, the urban intensity pattern of Beijing is strongly influenced by policies on historical and cultural heritage as well as environmental protection. For the former, the historical preservation requirements represented by the Conservation Plan for the Historic City of Beijing have protected the old city and its adjacent areas, located in the center of the city, from any modern developments with high-rise buildings. A representative area is the Forbidden City, a World Heritage site located in the city’s geometric center and surrounded by dense shopping and cultural facilities. However, the low FAR in and around this area contrasts with its dense distribution of business and shopping services under the strict building height restrictions required for historic preservation. In the latter case, environmental protection norms largely determine the upper limit of urban intensity for ecological protection and quality-of-life enhancement purposes. This cap is sometimes extremely rigid, covering areas such as river corridors, ecological control zones, mountainous areas, permanent farmland, and high-voltage corridors, where ecological and physical safety concerns strictly limit urban intensity. In other cases, the upper limits are flexible, mainly related to historical landscapes, the city axes, and open space, along with specific areas subject to general guidelines for buildings’ sunlight and ventilation requirements, although the room for flexibility is usually minimal.
Finally, the policy factors affecting urban intensity mainly include overall FAR interval restrictions, localized particular policies, and FAR incentives and transfer policies. Among them, overall restrictions are imposed out of consideration for the current urban situation, urban development goals, and urban problems, with the dual objectives of achieving control of urban growth extent and improving the intensity of land use. Localized particular policies are specific policies pursued in a particular area to solve urban problems and regulate future development. They exogenously change the urban intensity of these areas. Typical examples are the Tiantongyuan and Beiyuan areas, which were built in the early 2000s to solve housing problems in the then-fringe urban areas as affordable housing communities and thus have an extremely high FAR. FAR incentives and transfers regulate urban intensity on a local scale to achieve goals such as the preservation of historical and cultural blocks and the optimized use of public space. For example, the Tokyo Metropolitan Government’s Policy on the Application of Urban Development Systems for New Urban Development improves the urban environment. It induces urban development by relaxing the morphological restrictions stipulated in the Basic Building Law, such as FAR, building density, height, and slant line regulations. Similar measures, although not formally institutional, exist in Beijing and create outliers in the urban intensity landscape.

5.3. Planning Implications

For the ad hoc problems in urban intensity, the analysis of the difference between the status quo FAR and the ideal projections in this paper leads to direct planning implications. For example, the high intensity in Chaoyang city center has caused a regional public service shortage, which should be alleviated by increasing the supply. As another example, the high FAR of the two mega residential communities of Tiantongyuan and Beiyuan is not commensurate with their low levels of public and shopping services and transportation infrastructure provision and should also be targeted in near-future action plans. In contrast, Changping New Town, as a new urban area still under development, still shows some potential to raise the FAR and is worthy of attention in future urban planning.

More generally, this paper sheds light on the future reform of planning institutions from a methodological point of view. In preparing urban master plans and detailed regulatory plans, the urban intensity distribution can be predicted through the weighted overlay of the MCR model based on three factors: the accessibility of public services, the accessibility of planned employment-intensive areas, and land development costs. Policy, historical and ecological conservation, and implementability should be further considered as the basis for intensity formulation in urban planning.

5.4. Limitations and Prospects

It should be noted that the city, as a large, complex, and dynamic system, is difficult to fully adapt to the specific situation of each parcel by relying only on model calculations, which is an unavoidable limit of big data-based prediction. Therefore, the urban intensity calculation method proposed in this paper involves calibrating a reference value for urban planners and should not be treated too rigidly, and planning practitioners are advised to flexibly master the methodological framework, not the result figures per se of the paper, to adapt to their specific contexts.

Additionally, in terms of the explanation of the status quo deviation of urban intensity distribution from the “theoretical” predictions, we have focused on economic, geographical, and other ad hoc factors, as stated earlier. However, subtle social interactions may also contribute to the fine-grained heterogeneity of urban intensity, of which an explanation may be traced back to the classic sociological works of the Chicago school [66]. The lack of coverage of theories of this type is certainly a major limitation in our narrative and is also one we would like to address in more depth in future studies.
6. Conclusions

In this paper, to explain the deviation of the urban intensity distribution of Beijing from the classic economic geography location theory model, we took Beijing’s Chaoyang and Changping districts as case studies and utilized multisource big data and geospatial data to construct empirical models for explaining the city’s urban intensity formulation mechanisms. Along with the comparison with a series of “ideal” scenarios of urban intensity patterns, which were implied by applied economic geographical theories, we found that the pattern of the urban intensity distribution in Beijing generally still reflects the logic of economic geography location theories. However, factors such as the temporal mismatch of regional development under a strong planning orientation and historical factors significantly distorted the theoretical predictions, causing the urban intensity distribution in Beijing to present a seemingly unusual picture. We also found that problems in Beijing’s current urban intensity distribution appeared to have led to a lack of public service provision and a decline in residential utility. These findings are of potential significance regarding their implications for future urban planning of the city and may shed light on applied economic geographical theories, especially in a transition economy context.

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