Build up a Metropolis: Land Use Regulations, Spatial Misallocation, and Welfare*

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Abstract

We examine the general equilibrium effect of land use regulations within a city using a novel inner-city structure model that integrates both endogenous benefits and costs of urban agglomeration. Utilizing this model alongside a newly constructed, spatially disaggregated dataset for Shanghai, we uncover spatial misallocations of floor space caused by the city's land use regulations diverging from market demand. Allowing market forces to determine the land allocation between business and residential uses could improve welfare by 6.7%. An additional 2.4% could be gained by lifting height restrictions. These welfare gains primarily stem from improved production and consumption agglomeration economies and reduced housing costs. This paper also offers crucial insights for the future spatial development of expanding metropolises like Shanghai. While aligning regulations with market demands boosts efficiency typically, governmental interventions may be essential to address coordination failures resulting from a city's historical layout that presents spatial misallocation. Specifically, regarding constructing an additional 270 million sqm of new floor space as outlined in Shanghai's Master plan 2017-2035, we find that by prioritizing new land development in subcenters, welfare could be raised by 21.1%. This gain surpasses a citywide market-driven approach by 6.2%. The additional gains primarily result from enhanced productivity and residential amenities and reduced commuting costs.

JEL Classification: O18; R12; R31; R52

Keywords: Land use regulation; Spatial misallocation; Agglomeration economies; Urban Costs; Commuting congestion; Construction Cost; Quantitative urban model

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1. Introduction

Land use regulations are prevalent in both developed and developing countries. There has been extensive research on the effects of land use regulations on housing supply, real estate prices, city shape, and economic growth in the United States, Europe, India, and China (Glaeser et al., 2005; Saiz, 2010; Turner et al., 2014; Brueckner et al., 2017; Cai et al., 2017; Hsieh and Moretti, 2019; Harari, 2020; Tan et al., 2020, among others).[1] Although evidence has suggested market distortion caused by land use regulations in various studies, the general equilibrium effect of land policies via reshaping the spatial organization of economic activities within a city remains unclear, and the quantitative evaluation of their welfare implications is limited.[2]

Evaluating land use policies for cities is challenging because it requires balancing the fundamental trade-off between two externalities: agglomeration benefits and costs. On the one hand, high-density land development can enhance the positive externalities of agglomeration economies. On the other hand, high residential and workplace employment densities are likely to generate congestion, which plagues many global metropolises. For instance, Shanghai, one of China's most densely populated cities, has an average travel speed of merely 25 km per hour. Other populous cities worldwide, such as Manila, London, Tokyo, and Mumbai, face similar challenges, with travel speeds hovering between 19 km per hour and 26 km per hour.[3] Also, high densities tend to induce the construction of tall buildings, escalating construction costs. Notably, according to Ahlfeldt et al. (2023), the costs of height are particularly pronounced in many East Asian cities. Furthermore, the benefits and costs of agglomeration may influence residential and workplace location choices in a reverse way (Duranton and Puga, 2020). Although there have been recent works (see Allen, Arkolakis, and Li, 2016; Acosta, 2021; Gechter and Tsivanidis, 2023; Koster, 2024) that study land policies in a spatial GE framework considering endogenous positive externality of agglomeration as in Ahlfeldt et al. (2015), few works in the current literature seriously consider endogenous urban costs when evaluating land use regulations.

This paper examines the general equilibrium effect of land use regulations within a city using a novel model of internal urban structure that has both the benefits and costs of urban agglomeration to be endogenous to the spatial layout of jobs and people. Our model has three distinctive features: first, it

[1] For a review of the studies on land use regulations, see Gyourko and Molloy (2015).

[2] Allen, Arkolakis, and Li (2016), Acosta (2021), Gechter and Tsivanidis (2023), and Koster (2024) are notable examples of such attempts.

[3] The travel speed data for Manila, London, Tokyo, and Mumbai are metropolitan-wide and obtained from the 2023 annual report released by TomTom, a geolocation technology company. The speed statistics are drawn from data collected from over 600 million in-car navigation systems and smartphones. The travel speed data for Shanghai is from the 2023 China Urban Transportation Report published by the Baidu Map Open Platform.

incorporates the congestion effects of densities on bilateral commuting times, in addition to the positive agglomeration economies. Second, it allows the unit construction cost to be a function of the building height while considering the impact of geological characteristics, inspired by the empirical findings of Ahlfeldt and McMillen (2018) and Ahlfeldt et al. (2023). Thirdly, it incorporates endogenous public goods provision financed by net rental income, a common practice in many cities worldwide where local governments rely on land sales to finance public goods provisions. This extension allows land use policies to influence local amenities through public goods provision.

We apply our model to study the land use regulations in Shanghai, the most populous city with the highest GDP in China. This paper focuses on Shanghai due to the city's resemblance to numerous global megacities grappling with high population densities, constrained land availability, and severe traffic congestion. Furthermore, the city government of Shanghai enforces stringent land use regulations, a common practice in many Chinese cities, especially within the top 20 largest cities with over 10 million residents as of 2020. In particular, the city government imposes zoning restrictions on land use types in each street tract, generating an endogenous price wedge between business and residential land. It also regulates housing development densities on each land parcel through the floor-to-area ratio (FAR hereafter)[4]. A comprehensive assessment of the efficiency of these regulatory measures is crucial in advancing urban welfare.

Moreover, similar to other cities in China and the developing world, Shanghai faces an urgent need to expand its construction space. The city government guides the allocation of new land development by issuing development quotas across various localities within the city, a decision that will significantly reshape the spatial distribution of economic activities in Shanghai. Providing insights on devising new land development strategies for such cities while considering the constraints imposed by their historical layouts is of paramount importance.

We first construct a dataset of Shanghai at the most disaggregated administrative-unit level, i.e., the street tract (*jiedao* or *zhen* in Chinese) level. The dataset includes information on each street tract's residential and workplace employment, FARs, land use types, housing prices, land prices, wages, and local attributes. It also has each bilateral tract pair's commuting flow, commuting time, and cross-traffic flow measures in the city's road network. This dataset helps us document the city's current spatial patterns of land use and economic activities. Using the above data, we then estimate and calibrate the model's parameters, including each street tract's exogenous fundamental amenities.

4 This paper adopts the term "building height restrictions" to represent FAR constraints, as in Brueckner et al. (2017). We view height and density restrictions as interchangeable concepts, acknowledging the nuanced distinction between height and density.

Relating each street tract's productive and residential fundamental amenities to its floor space supply, we find evidence suggesting misallocation caused by Shanghai's existing land use regulations. First, each street tract's zoning restrictions on land use types do not reflect the local comparative advantage. The estimated price wedges between business and residential land indicate that the city government of Shanghai oversupplied business land in more than 60% of the street tracts, especially in localities with a higher comparative advantage in residential fundamental amenities compared to production ones. Second, each street tract's overall floor space supply has no correlation with local fundamentals. These fundamentals, whether productive or residential, are the main driving factors for housing market demand. The above misallocations may lead to considerable welfare losses, which this paper will gauge.

We then conduct counterfactual analyses using our model that allow the market to play a more significant role by lifting zoning restrictions and building height constraints in Shanghai while fixing the land development area at the existing levels.[5] Our analysis also sheds light on the channels that contribute to the changes in welfare, such as changes in local productivity and residential amenities due to agglomeration economies, changes in housing prices, and changes in commuting costs resulting from the congestion effect.

First, we relax the zoning restrictions on land use types while keeping each street tract's building height constraints unchanged. Free arbitrage then determines endogenously the share of business land versus residential land. The welfare gain relative to the benchmark level is 6.7%. The allocation of land between different use types under this scenario better reflects the local comparative advantage, fostering increased agglomeration of jobs and residents in areas rich in desirable production and residential attributes, respectively, thus leading to increased wages reflecting heightened productivity and improved living amenities on average. Housing prices are lowered because, initially, the city oversupplies business land. Our finding echoes the findings of Henderson et al. (2022) at the city level, which suggests that removing the favoritism of land allocation on business use can generate a welfare gain of 8.1%.

Second, we further lift the building height constraints so that the developers can set their own building heights to maximize the value per unit of land following market price signals and construction costs. Because the supply of floor space in each locality now responds to market demand, those

[5] In China, the land development area is regulated by land quota, which is allocated through a top-down administrative hierarchy. The quota allocation depends on historical, geographical, economic, and political factors. Typically, a city's existing land quota allocation is guided by a city's long term development plan and implemented strictly. Therefore, it is hard to change in the short term.

localities that are more attractive either for production purposes or for residential purposes get more floor space supply; this strengthens the agglomeration of jobs or residents in those localities and further enhances both the productivity and living amenities there. Consequently, both the average wage and residential amenities increase compared with the previous counterfactual that just removes the zoning restriction. This further relaxation brings an additional welfare gain of 2.4%, leading to an overall welfare gain of 9.1% compared with the benchmark. Notice that in the above welfare calculations, we do not consider the demolish costs involved in the redistribution of floor space supply across locations within the city. One may think of the welfare gains in the above counterfactuals as the flipside of welfare losses caused by the city's existing regulations on land use types and building heights that diverge from the market demand.

Planning future spatial development is of eminent importance for a metropolis like Shanghai, where the city construction space is undergoing expansion. A critical challenge is the constraint of the existing urban structure, which cannot be ignored due to the substantial economic and social costs associated with demolishing old buildings and relocating people and firms (Wang, Zhang, and Zhou, 2020). Next, this paper focuses on Shanghai's land development in the future and offers insights for designing more efficient land policies, using the above theoretical framework and calibrated or estimated parameters as a workhorse.

According to Shanghai's 2017-2035 Master Plan, an additional 270 million square meters of floor space will be built on top of the existing floor space stock of 1,050 million square meters between 2015 and 2035, representing a roughly 30% increase. Correspondingly, a large amount of new land development quotas will be granted, making the allocation of these new quotas across Shanghai an important decision, alongside zoning restrictions and building height constraints. We focus on exploring various land quota allocation plans under the constraint that the existing floor space layout remains unchanged. Informed by our previous analysis, we propose lifting the zoning restrictions on land use types and allowing market forces to determine the heights of buildings on the new land to be developed.

We simulate the corresponding equilibria under various development plans. Firstly, we allow market forces to determine the distribution of new floor space. This market-oriented plan yields a welfare gain of 14.9% compared to the initial benchmark level. Secondly, we explore alternative plans where the city government only grants development quotas to selected regions within the city. Specifically, we evaluate a heavily debated candidate plan that permits developers to undertake new land development solely in the nine subcenters of Shanghai, located 10-20 km from the city center. These subcenters are notable for their commendable local production and residential fundamentals. Prioritizing development in these subcenters considerably stimulates agglomeration economies, resulting in substantial gains in both productivity and living amenities compared to the purely market-oriented development plan. Furthermore, commuting distances and times are significantly reduced. Overall, the welfare gain rises to 21.1% compared to the initial benchmark level, surpassing the gains from the non-government intervention plan by 6.2%.

Our findings suggest that prioritizing the development of subcenter regions is a sensible approach for Shanghai's future growth. Why is this? Given the historical constraint of an existing floor space layout with spatial misallocation, the initially less densely developed subcenters may appear less attractive to people and jobs following market signals compared to other initially densely populated locations, even though the subcenters have better fundamentals. As a result, the potential of agglomeration economies may not be fully realized. Moreover, while the historically high-density locations become increasingly congested, market forces may not fully account for this negative externality. Therefore, given these historical constraints, it may be beneficial for the city government to prioritize the development of subcenters for the future. Such a development plan could help overcome coordination failure due to externalities and, in turn, enhance welfare compared to a purely market-oriented development.

Our paper makes contributions to several strands of literature. Firstly, a large body of literature investigates the effects of various land use regulations (for a review, see Gyourko and Molloy, 2015).[6] Existing studies have found substantial effects of regulations on the quantity and price of local housing[7] and have documented strong relationships between land use constraints and the spatial sizes of cities.[8] Within this literature, our paper is closely related to the papers that draw efficiency implications of land use regulations, such as Bertaud and Brueckner (2005), Glaeser, Gyourko, and Saks (2005), Turner, Haughwout, and van der Klaauw (2014) and Cai, Wang, and Zhang (2017). Our paper adds to this literature by developing a quantitative spatial equilibrium model incorporating both the benefits and costs of urban agglomeration. Simulations show that without considering the congestion costs, the model's explanatory power for the actual data would be lower. Moreover, the predicted welfare changes under the alternative model would be much larger than those predicted by the baseline model, and the redistribution of people and jobs would be too polarized to be realistic. Our baseline framework allows

[6] These regulations include height or density restrictions, caps on the number of housing units built or permitted, population growth limits, urban boundaries, zoning restrictions, and delays in local governmental approvals.

[7] For example, see Quigley and Rosenthal (2005), Saks (2008), Glaeser et al. (2008), Glaeser and Ward (2009), Saiz (2010), Zabel and Dalton (2011), Hilber and Vermeulen (2016), and Baum-Snow and Lu (2024).

[8] For example, see Pasha (1992), Bertaud and Brueckner (2005), Song and Zenou (2006), Brueckner and Sridhar (2012), Geshakov and DeSalvo (2012), Harari (2020), and Wang et al. (2020).

for a more comprehensive evaluation of the general equilibrium effects of land use policies within a city, facilitates the investigation of the spatial redistribution of economic activities, and delves into the various channels that may cause the changes in welfare levels.[9]

Moreover, while previous studies have primarily focused on inefficiencies arising from regulations governing the scale and intensity of land development, we explore an additional misallocation caused by regulations on land use types. Henderson, Su, Zhang, and Zheng (2022), in their pioneering study on this misallocation, investigated how city governments' manipulation of land allocation between different uses can lead to welfare losses at the city level. In this paper, we examine the efficiency of zoning restrictions on land use types within a city at the street-tract level.

Secondly, our paper is related to the literature that addresses the importance and challenges of urban land planning for cities experiencing increased demand for redevelopment and spatial expansion. For instance, Henderson, Regan, and Venables (2021) presented a comprehensive framework that delineates the dynamic nature of urban structures in African cities, suggesting that institutional frictions may hinder the upgrading of slums to achieve more efficient land use. Harari and Wang (2024) explored policy interventions aimed at upgrading slum areas in Indonesian cities. Gechter and Tsivanidis (2023) studied the redevelopment of old industrial plots in India and its general equilibrium impact. Loumeau (2024) examined the effect of developing edge cities on inner-city structure and urban growth through the lens of a spatial GE framework. Wang, Zhang and Zhou (2020) investigated the political reasons underlying the urban expansion pattern of Chinese cities and highlighted the high redevelopment costs in the central city relative to the new development costs in the outer rings. Our paper contributes to this literature by formulating pragmatic guidelines for future land development in an expanding metropolis like Shanghai, where the costs associated with redevelopment are very high. Using a novel model that integrates endogenous agglomeration economies, accounts for congestion externalities, and incorporates construction costs, this paper demonstrates that although aligning land use regulations with market demands can enhance welfare, the misallocation presented by the historical constraints of the existing urban structure justifies government intervention in allocating new land development quotas to overcome coordination failures. Essentially, our proposal advocates for a sensible combination of the invisible hand (market forces) and the visible hand (government intervention) to sculpt an optimal urban structure—a new perspective in the field of urban land

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[9] In addition to agglomeration externalities, commuting congestion, and housing price, land development policies may also affect welfare through some other important channels, such as social interactions (e.g., Putnam, 2000; Glaeser and Gottlieb, 2006; Brueckner and Largey, 2008) and health (e.g., Ewing et al., 2003; Lopez, 2004; Eid et al., 2008). We will leave the discussion for future research.

planning.

Thirdly, a body of literature examines the impacts of urban determinants on commuting outcomes such as travel speeds, travel distances, and travel times. Notable studies in this area include Gordon et al. (1989), Giuliano and Small (1993), Bento et al. (2005), Brownstone and Golob (2009), Duranton and Turner (2011, 2018), and Akbar, Couture, Duranton, and Storeygard (2023a, b). In particular, Akbar et al. (2023b) show that urban population density significantly impacts urban commuting speed and congestion factor at the city level using a global database on motor vehicle speed in over 1,200 large cities in 152 countries. Recent studies integrate endogenous congestion to study the impact of urban transportation policies (Brinkman, 2016; Zhang and Kockelman, 2016; Allen and Arkolakis, 2022; Barwick, Li, Waxman, Wu, and Xia, 2024). Our paper makes a valuable contribution by analyzing Chinese data at a more detailed spatial scale, explicitly estimating the impact of the spatial arrangement of residential and workplace employment densities along transport networks on bilateral commuting times. We then incorporate endogenous congestion into a unified framework to quantitatively evaluate various land regulation policies, utilizing the congestion elasticities estimated above.

Fourthly, our paper aligns with the existing literature on how the spatial distribution of people and jobs affects local amenities. This literature has examined both production amenities, as reviewed by Rosenthal and Strange (2004), Duranton and Puga (2004), Moretti (2011), and Combes and Gobillon (2015), and consumption amenities, as discussed by Glaeser, Kolko and Saiz (2001), Couture and Handbury (2020), Baum-Snow and Hartley (2020), Brinkman and Lin (2024), Su (2022), and Couture, Gaubert, Handbury, and Hurst (2024). Consistent with this literature, our paper allows localities within a city to have different production and residential amenities that are endogenous to the spatial distribution of residential and workplace employment. Unlike the previous works, we also endogenize public goods provision to land development policies, an essential factor influencing local amenities as well.

The rest of the paper is organized as follows: Section 2 describes the institutional background of urban land use regulations and planning in China, Shanghai's current spatial organization, and the city's 2017-2035 Master Plan. In Section 3, we present our theoretical framework. Section 4 discusses the data and describes the basic spatial patterns of economic activities in Shanghai. Section 5 estimates some key parameters of our model. In Section 6, we calibrate four sets of model parameters. Section 7 presents counterfactual analyses of relaxing zoning restrictions on land use types and building height constraints, illustrating significant welfare losses due to misallocation caused by current regulations. In Section 8, we evaluate various plans for Shanghai's future land development. Section 9 discusses an alternative model without the endogenous congestion effect. Finally, Section 10 concludes.

2. Background

This section outlines the common land use regulations in Chinese cities, with a focus on Shanghai. Moreover, we present Shanghai's spatial organization and introduce the city's land development Master Plan from 2017 to 2035.

2.1 Land use regulations in Chinese cities

In China, a typical prefecture city comprises a central city (*shi xia qu*) and surrounding rural counties (or county towns). Within the central city, each urban district administers several street tracts (*jie dao* in Chinese), the lowest level of political divisions. The state owns all urban land in Chinese cities.[10] Since 1998, China has implemented an urban land quota system through a hierarchical, top-down planning process. The central government creates the nation's long-term land development plan, which specifies the maximum amount of newly developed urban land for each province in the long term and the minimum amount of rural arable land to be held in reserve. Provincial governments then create their long-term development plans and also make short-term (five-year or annual) land development plans. According to these plans, provincial governments then assign land development quotas to cities within their administrative jurisdiction. The newly developed land originates from two primary sources: rural-to-urban land conversion beyond a city's limits and the clearance of vacant or wasteland areas within the city's boundaries.

Given the total land quota, the city government has considerable discretion regarding where and how to develop across different locations within a city. In a typical Chinese city, the land reserve and allocation committee is responsible for general land use planning and guideline setting. The committee's members include the city's key leaders and bureau directors from relevant government agencies. The objectives are promoting efficient land use, guarding "public interest," and protecting historical heritage and natural resources.

After establishing the urban development strategies and guidelines, which often involve deciding on prioritized development locations and allocating land quotas for new development, the committee typically delegates routine decisions, such as land use type (e.g., residential, commercial, or industrial use) and detailed restrictions on FAR[11], green space ratios, and open areas, to the city's urban planning

[10] The rural and urban sectors are under separate institutional and economic regimes in China (Naughton, 2017). Land in the rural area surrounding the central city is owned by rural collectives.

[11] Floor-to-area ratio (FAR) is the total floor space built on a land parcel divided by the total land area. In order to regulate building height/density, the city government typically imposes an upper limit on FAR, which specifies the maximum floor space that can be built per unit of land (Brueckner et al., 2017; Cai et al., 2017).

commission for each parcel of land to be developed. In essence, the floor space supply in each locality of the city is largely determined by how much land development is permitted in the locality as well as the housing development height/density regulations (i.e., FAR limits). Previous literature has documented that the building density restrictions in Chinese cities are too stringent, especially in more attractive locations, leading to increased housing prices there (Cai et al., 2017; Gu et al., 2017; Tan et al., 2020).

The distribution of floor space across various use types, such as industrial, commercial, and residential, is another critical regulation under the control of local governments. Research has revealed that local governments often underprice land for industrial purposes to attract business by over-allocating it, as documented by Tao et al. (2010) and Henderson et al. (2022). According to Tian et al. (2024), over half of the newly transacted urban land is allocated annually for industrial use. In addition to the land misallocation between industrial and residential use at the city level (Henderson et al., 2022), there is also significant misallocation within cities, where land intended for business is often located in areas with weak business growth potential. For example, Chen et al. (2024) discovered that more high-office buildings were constructed in suburban areas with inadequate initial business environments during the post-2009 period. Furthermore, a Financial Times article reported that the office market vacancy rate in 17 significant Chinese cities exceeded 20% in 2019.[12] Since 2022, many local governments have promoted reforms that increase flexibility in adjusting land use type for a given land parcel to meet market demand better.

As a provincial-level city, Shanghai has 16 urban districts and no rural counties since 2015. Land use regulations in Shanghai are typical as in other Chinese cities. The city government designates how much land is to be developed across different localities under the guidance of the city's general development plan. The city planning bureau sets regulatory development density constraints for each land parcel. According to our data, the average FAR is just 1.85, much lower than the FARs in other metropolises in the world, such as New York, Singapore, Seoul, and Hong Kong (Bertaud, 2011). Each urban district in Shanghai has its own zoning restrictions that regulate the land allocation across use types within that district, creating varying price differentials between business and residential land. Of Shanghai's 209 street tracts, 138 have business land prices significantly lower than residential land prices, with the average ratio of business to residential land price being 0.487. This indicates a prevailing inclination towards business development over residential development in the city.

2.2 The spatial organization of Shanghai

[12] See https://www.ft.com/content/edce2600-f0a0-11e9-ad1e-4367d8281195.

The urban districts of Shanghai are further divided into a total of 209 street tracts. A street tract is the most disaggregated spatial unit for which information on workplace employment and bilateral commute flow is available. The mean area of Shanghai's street tracts is approximately 32 square kilometers, while within the 30 km ring around the city center, there are 144 street tracts with a mean area of about 16 square kilometers. The larger street tracts are typically in suburban districts. They possess more vacant land for development in general. As of 2015, Shanghai's population is 24.15 million, and its GDP per capita is 103,796 yuan. The GDP shares of the secondary and tertiary sectors are 31.8% and 67.8%, respectively, and the employment shares of these two sectors are 34% and 63%, respectively.

Before the launching of urban reforms in the 1990s, there was no land market. Housing for urban residents was provided by their employers (work units), and most urban industry and city residents were located in the central city. As a consequence, the separation of workplace and residence was not prevalent, and commuting congestion was not a significant issue. Land, housing, and labor market reforms in the 1990s facilitated the mobility of firms and people, triggering the redistribution of population and jobs within Chinese cities. Since 1990, the spatial sizes of Chinese cities have been expanding rapidly, driven by local economic growth and the promotion incentives of city politicians (e.g., Deng et al., 2008; Lichtenberg and Ding, 2009; Wang et al., 2020). The administration division reforms, including those annexing rural counties into the central city ("*che xian she qu*" or "*che xian she shi*" in Chinese), have also helped convert surrounding rural land to urban use, providing the city government with new vacant land for development at the city edge (Tang and Hewings, 2017). Furthermore, the large-scale construction and rapid growth of the urban railroad and highway networks have caused the decentralization of production in Chinese cities (Baum-Snow et al., 2017).

Consequently, the separation of workplace and residence has become prevalent, and car ownership has increased sharply. Long commuting times and traffic congestion have become a norm of life, especially in the megacities of China. According to the 2023 China Urban Transportation Report published by Baidu Map Open Platform, the average one-way commuting time was 40 minutes in Shanghai, the second longest among all Chinese cities.[13] The average commuting speed was 25 km per hour, much slower than the average speed in the U.S. (45 km per hour), suggesting heavy congestion.

According to the 2020 Shanghai Transportation Annual Report, released by the Shanghai Institute of Urban and Rural Construction and Transportation Development, in 2019, about 33% of commuters relied on public transit, typically subways, 27% used cars or taxies, 24% preferred walking and 16%

[13] See huiyan.baidu.com/reports. The first longest was Beijing, with an average one-way commuting time of 44.5 minutes. Beijing's average commute speed was 24 km per hour in 2023.

chose biking.[14] Those who walk or bike to work are short-distance commuters. Our commute flow data show that about 67% of Shanghai's commuters travel across street tract boundaries, and their average bilateral one-way commute distance is about 14 km. For these cross-tract commuters traveling more than 10 km, 31% use cars, 33% use subways, and 18% use buses, according to the 2015 Population Census data.

Notably, Shanghai has a well-developed subway network, with a total length of subway lines was 705 km and 415 subway stations as of the end of 2018. The average daily ridership in 2019 reached 11 million, as reported by the Shanghai Municipal Transportation Commission.[15] Congestion in the subway mainly occurs at the starting and ending points when people enter or exit the subway stations. In rush hours, it may take as long as 10-20 minutes waiting in line to get on the train in a busy station.[16]

For commuters who rely on cars (and long-distance bus travel), over 80% of the commute routes recommended by the popular navigation APPs utilize elevated highways ("*gao jia kuai su lu*") or controlled-access freeways ("*gao su lu*"). Not surprisingly, most congestion happens at the entries and exits of highways/freeways. Therefore, in Shanghai, the population or job densities at the starting and ending points of any bilateral route should be important determinants of congestion degree along this route. This feature differs from the situation in Seattle, where the majority of commuters travel by car on local roads, resulting in travel speeds primarily influenced by cross-traffic flows along road segments (Allen and Arkolakis, 2022). In Shanghai, cross-traffic flows also affect commute speed on the highways/freeways, primarily through the slowdown at specific traffic bottlenecks along the routes.[17] These bottlenecks are junctions in the highway/freeway networks where commute routes pass through most frequently. We shall discuss this in more detail in Section 4.

2.3 The 2017-2035 Master Plan of Shanghai

Guided by the nation's long-term development plan, Shanghai's government creates its own land development plans. In January 2018, Shanghai announced the 2017-2035 Master Plan, which outlines its spatial development strategies, including housing, infrastructure, cultural and environmental protection, and industrial policies. The plan is made primarily according to each locality's geographic distance to the traditional city center and its initial conditions, such as population size and economic

[14] See sohu.com/na/417357304_468661.

[15] See jtw.sh.gov.cn/xydt/20200514/e815c562c36a491ba741d576a9bcac1f.html.

[16] See https://xueqiu.com/4198399524/124956105
and https://www.cnr.cn/shanghai/shzx/ms/20180317/t20180317_524167886.shtml.

[17] See https://baijiahao.baidu.com/s?id=1582186212387073357&wfr=spider&for=pc.

conditions.

The plan delineates the spatial boundaries of one core urban area around the city center and nine subcenters surrounding the core urban area. The core urban area consists of 35 street tracts, all within the 10 km ring around the city center, where commercial densities are high. The boundary of each of the nine subcenters overlaps with one street tract in our sample. Among the nine subcenter street tracts, three are within the 7-10 km belt from the city center, two within the 10-15 km belt, three within the 15-20 km belt, and one 23 km from the city center. Additionally, the plan identifies five edge towns near the city's fringe where the government will invest heavily in infrastructure in the coming years. These five towns are in Jiading, Songjiang, Qingpu, Fengxian, and the southern point of Pudong New District. Figure 1 illustrates the spatial layout of the core urban area, subcenters, and edge towns on the map of Shanghai.

[Figure 1 about here]

The plan outlines urban land development goals, aiming to increase an additional 270 million square meters of floor space by 2035 in addition to the current 1.05 billion square meters of total floor space. The plan proposes that the city can expand its current urban land stock by at most 4.2% to accommodate new constructions for residential and business development, transportation and public infrastructure, and green spaces.[18] While the spatial allocation of these new land development quotas is yet to be determined, priority will likely be given to subcenters or edge towns. It is worth noticing that in order to safeguard valuable resources such as high-quality farmland, cultural and historical sites, ecological zones, and water conservation areas, the Master Plan imposes strict boundaries for urban development. Construction beyond these limits is prohibited. Of particular note is the allocation of much of Chongming Island for non-urban development, including agricultural areas, forests, and wetland reserves, as indicated by the plan's development boundary map.

Another noteworthy aspect of the plan is the city government's goal to manage population growth rigorously. The objective is to limit the population to around 25 million by 2035 through implementing various restrictions. It is worth noting that Shanghai had 24.15 million people in 2015.

3. Model

We consider a city with a fixed population (or workers), H.[19] The city consists of a set of discrete street tracts, which are indexed by $i = 1, \dots, S$. These street tracts differ in productivity, residential amenities,

[18] According to the Master Plan, the initial construction land stock is 3,071 square kilometers, as recorded in 2015.

[19] Because of the stringent *Hukou* policy implemented in Shanghai, we assume the city's population is fixed.

land use regulations, and location in the transport network. Each street tract's productivity and residential amenities are in part determined by its local fundamental amenities (e.g., transport connections, schools, hospitals, roads, green coverage and etc.) and in part determined by agglomeration forces (e.g., the spatial concentrations of residents and jobs). Each street tract's overall supply of floor space L_i is determined by the city planner through land use regulations. Moreover, the city government also dictates the allocation of land between residential and business use for each street tract. We denote the fractions of floor space allocated to residential use and business use (including both commercial and industrial purposes) by θ_i and $1-\theta_i$, respectively, which are determined by the fraction of land and the building height regulations for each use type. The local government collects the rental income net of construction costs to provide public goods, which increases the local fundamental amenities. Firms produce a single final good, which is freely traded within the city and the larger economy and is chosen as the numeraire ($p = 1$). Each worker selects the pair of residence and workplace street tracts within the city that maximizes utility after observing idiosyncratic utility shocks to each possible pair of residence and workplace street tracts. The commute time of each bilateral street tract pair is determined by the densities of workers at both the residence and workplace street tracts and the cross-traffic flow at the bottlenecks along the shortest bilateral route connecting the two street tracts in the road network, in addition to the bilateral distance and transport infrastructure.

3.1 Workers

The utility of worker k who lives in street tract i and works in street tract j is

$$U_{ijk} = \frac{B_i z_{ijk}}{d_{ij}} \left(\frac{x_{ijk}}{\beta}\right)^{\beta} \left(\frac{l_{ijk}}{1-\beta}\right)^{1-\beta} \tag{1}$$

where B_i represents residential amenities of street tract i; x_{ijk} is the consumption of the final good; l_{ijk} is the consumption of residential floor space; d_{ij} represents the disutility from commuting from residence street tract i to workplace street tract j ($d_{ij} > 1$); z_{ijk} is an idiosyncratic utility shock that is specific to individual worker k and varies with the worker's choices of residence and workplace pair.[20]

We assume that the disutility from commuting has the following functional form:

$$d_{ij} = e^{\kappa * \tau_{ij}} \tag{2}$$

It increases with the travel time τ_{ij} between street tracts i and j. The parameter κ is the semi-elasticity of commuting costs w.r.t. commuting time.

Following McFadden (1974) and Eaton and Kortum (2002), we assume that each worker's

[20] This random draw captures the idea that individual workers can have idiosyncratic reasons for living and working in different parts of the city.

idiosyncratic utility drawn from any residence and workplace pair (i.e., street tracts i and j) follows an extreme value distribution:

$$F(z_{ij}) = e^{-z_{ij}^{-\varepsilon}} \tag{3}$$

The shape parameter $\varepsilon > 1$ reflects the dispersion of the idiosyncratic utility; a larger ε implies smaller dispersion of these random draws, which implies that workers' location decisions are more sensitive to differentials in economic fundamentals across street tracts (including wages, residential amenities, housing costs and commuting costs), rather than idiosyncratic preferences.

The indirect utility from residing in street tract i and working in street tract j can be expressed in terms of the wage paid at this workplace w_j, commuting costs d_{ij}, the residential floor price Q_i, the residential attractiveness B_i, and the idiosyncratic shock z_{ijk}:

$$U_{ijk} = \frac{z_{ijk} B_i w_j Q_i^{\beta-1}}{d_{ij}} \tag{4}$$

After observing the realization of idiosyncratic utility for each pair of residence and workplace street tracts, each worker chooses where to live and work to maximize the utility, taking wages, residential amenities, housing prices, commuting costs, and the location decisions of other workers and firms as given. Because the random utility shock has a Frechet distribution, the probability that a worker chooses to live in street tract i and work in street tract j is

$$\pi_{ij} = \frac{\left(d_{ij} Q_i^{1-\beta}\right)^{-\varepsilon} (B_i w_j)^{\varepsilon}}{\sum_{r=1}^{S} \sum_{s=1}^{S} \left(d_{rs} Q_r^{1-\beta}\right)^{-\varepsilon} (B_r w_s)^{\varepsilon}} \equiv \frac{\Phi_{ij}}{\Phi} \tag{5a}$$

The overall probability that a worker resides in street tract i is

$$\pi_{Ri} = \sum_{j=1}^{S} \pi_{ij} = \frac{\sum_{j=1}^{S} \Phi_{ij}}{\Phi} = \frac{(B_i Q_i^{\beta-1})^{\varepsilon} \sum_{j=1}^{S} (w_j/d_{ij})^{\varepsilon}}{\sum_{r=1}^{S} \sum_{s=1}^{S} \left(d_{rs} Q_r^{1-\beta}\right)^{-\varepsilon} (B_r w_s)^{\varepsilon}} \tag{5b}$$

The overall probability that a worker works in street tract j is

$$\pi_{Mj} = \sum_{i=1}^{S} \pi_{ij} = \frac{\sum_{i=1}^{S} \Phi_{ij}}{\Phi} \tag{5c}$$

Conditioning on living in street tract i, the probability that a worker commutes to street tract j is

$$\pi_{ij|i} = \frac{\pi_{ij}}{\pi_{Ri}} = \frac{(w_j/d_{ij})^{\varepsilon}}{\sum_{s=1}^{S} (w_s/d_{is})^{\varepsilon}} \tag{6}$$

Using the conditional commuting probabilities in Eqn. (6), we equate the measure of workers employed in street tract j (H_{Mj}) and the measure of workers choosing to commute to street tract j to work. We thus obtain

$$H_{Mj} = \sum_{i=1}^{S} \pi_{ij|i} H_{Ri} = \sum_{i=1}^{S} \frac{(w_j/d_{ij})^{\varepsilon}}{\sum_{s=1}^{S} (w_s/d_{is})^{\varepsilon}} H_{Ri} \tag{7}$$

where H_{Ri} is the measure of residents in street tract i. It shows that the total number of workers commuting to workplace j to work is a continuously increasing function of workplace j's wage (discounted by commuting costs) relative to other locations. We can also write the expected wage of workers living in street tract i as

$$\mathrm{E}\left(w_j \middle| i\right) = \sum_{j=1}^{S} \pi_{ij|i} w_j = \sum_{j=1}^{S} \frac{(w_j/d_{ij})^{\varepsilon}}{\sum_{s=1}^{S}(w_s/d_{is})^{\varepsilon}} w_j \tag{8}$$

Assume that the total population of the city is fixed at H, then $\sum_{i=1}^{S} H_{Ri} = \sum_{j=1}^{S} H_{Mj} = H$. The expected utility of a typical worker in the city is:

$$\mathrm{E(u)} = \gamma[\sum_{r=1}^{S} \sum_{s=1}^{S} \left(B_r Q_r^{\beta-1}\right)^{\varepsilon} (w_s/d_{rs})^{\varepsilon}]^{1/\varepsilon} \tag{9}$$

where the expectation is taken over the distribution for the idiosyncratic utility shocks; $\gamma = \Gamma(\frac{\varepsilon-1}{\varepsilon})$ and $\Gamma(\cdot)$ is the Gamma function.

3.2 Production

Production of the final good is assumed to be perfectly competitive and constant returns to scale. We assume that the production technology takes the Cobb-Douglas form. The output of the final good of a representative firm in street tract j is

$$y_j = A_j H_{Mj}^{\alpha} L_{Mj}^{1-\alpha} \tag{10}$$

where A_j is final goods productivity and L_{Mj} is the measure of floor space used for production in street tract j.

Profit maximization gives the labor demand and the floor space demand in street tract j, respectively:

$$H_{Mj} = \left(\frac{\alpha A_j}{w_j}\right)^{1/(1-\alpha)} L_{Mj}\ , L_{Mj} = \left(\frac{(1-\alpha)A_j}{q_j}\right)^{1/\alpha} H_{Mj}$$

From the above first-order conditions and the zero profits condition, equilibrium business floor prices q_j in each street tract with positive employment must satisfy:

$$q_j = (1-\alpha)\left(\frac{\alpha}{w_j}\right)^{\alpha/(1-\alpha)} (A_j)^{1/(1-\alpha)} \tag{11}$$

3.3 Housing market

We assume that the floor space is produced by a housing sector that is subject to land use regulations. The supply of floor space at street tract i is

$$L_i = \varphi_i K_i^L \tag{12}$$

where φ_i is the density of development, which is regulated by building height constraints. We assume that such regulation is the same for business and residential development within each street tract. However, this assumption can be relaxed. The city government controls the floor space supply by either controlling the amount of land granted for development, denoted by K^L, or setting constraints on building height, denoted by φ_i. These are prevalent land use regulations in Chinese cities and are typically highly heterogeneous across different localities within a city (see Cai et al., 2017; Tan et al., 2020).

The construction cost in street tract i is

$$cost_i(L_i, \varphi_i) \equiv c_i(\varphi_i) \times \varphi_i \times K_i^L, \tag{13a}$$

where K_i^L is the construction land area, φ_i is building height, and $c_i(\varphi_i)$ is the unit construction cost, which increases with the building height, φ_i. Note that $c_i(\varphi_i)$ may depend on the geological conditions. In Shanghai, while the land surface remains predominately flat with minimal slope variation (with an average slope of 3.7 degrees and a standard deviation of 1.3 degrees), there exists notable diversity in the depth of bedrock beneath the surface. Moreover, the depth of bedrock in Shanghai ranges from 85 to 187 meters (excluding Chongming Island), far surpassing that of many other cities worldwide. Following Ahlfeldt, Baum-Snow, and Jedwab (2023), we allow the elasticity of unit construction cost w.r.t. building height, ec, to increase with the depth of bedrock when the depth falls short or exceeds a certain threshold $\overline{depth}$. As such, the unit construction cost function takes the form:

$$c_i(\varphi_i) = \bar{c} \times {\varphi_i}^{ec_i}, \tag{13b}$$

where $ec_i = e0 + e1 \times |depth_i - \overline{depth}|$ and $depth_i$ is the depth of bedrock under the ground at street tract i; $e0 > 0$, and $e1 \geq 0$.

As another important land use regulation in Chinese cities, city governments control the allocation of land between different uses in order to achieve policy goals such as GDP growth (Henderson et al., 2022). In particular, the city government designate θ_i of land supply in tract i to residential use and $(1 - \theta_i)$ to business use; moreover, the conversion from business land to residential land or vice versa after the land is auctioned off is strictly prohibited. Such zoning restriction generates an endogenous price wedge between business land and residential land, denoted by ξ_i^0, which is different from the exogenous tax-equivalent land price wedge specified in Ahlfeldt et al. (2015). Assuming that the building height constraint is the same across land use types, the residential floor space supply is $\theta_i L_i$ and the business floor space is $(1 - \theta_i)L_i$. Given that competitive bidding in the land market drives zero profits for developers, we can obtain the following relationship:

$$\frac{q_i}{Q_i} = \frac{\xi_i^0 pr_i + c_i(\varphi_i) \times \varphi_i}{pr_i + c_i(\varphi_i) \times \varphi_i} \tag{14}$$

where pr_i represents the price per unit of residential land.

Residential housing market clearance implies that the demand for residential floor space equals the supply of floor space for residential use in each location:

$$L_{Ri} \equiv \mathrm{E}(l_i)H_{Ri} = \theta_i L_i$$

where $E(l_i)$ is the expected residential floor space per worker in street tract i and it is equal to $(1-\beta)E(w_j|i)/Q_i$. By plugging Eqn. (8) into the equation above, we have

$$L_{Ri} \equiv H_{Ri}\left(\frac{1-\beta}{Q_i}\right)\sum_{j=1}^{S}\frac{(w_j/d_{ij})^{\varepsilon}}{\sum_{s=1}^{S}(w_s/d_{is})^{\varepsilon}}w_j = \theta_i L_i. \tag{15a}$$

Business housing market clearance requires that the demand for business floor space equals the supply of floor space for business use in each location:

$$L_{Mi} \equiv \left(\frac{(1-\alpha)A_j}{q_i}\right)^{\frac{1}{\alpha}} H_{Mi} = (1-\theta_i)L_i. \tag{15b}$$

3.4 Agglomeration forces

Next, we introduce the positive spillover effects on production and residential amenities generated by workplace and residence population agglomeration, respectively. We allow each street tract's final goods productivity (A) to depend on its own production fundamental amenities (a) and the production agglomeration economies that depend not only on its own employment density but also on the positive productive spillover effects from other street tracts (Y):

$$A_i = a_i Y_i^{\lambda},\ Y_i \equiv \sum_{s=1}^{S} e^{-\delta\tau_{is}}\left(\frac{H_{Ms}}{K_s}\right), \tag{16a}$$

where H_{Ms}/K_s is workplace employment density per unit of land area in street tract s; production spillovers decline with travel time (τ_{is}) through the iceberg factor $e^{-\delta\tau_{is}} \in (0,1]$; δ determines the rate of spatial decay; and λ captures the effect of the agglomeration economies on productivity. Note that production fundamentals are determined by exogenous physical geography features independently of a street tract's employment density or surrounding areas' densities of economic activity.

Similarly, we allow residential amenities (B) to depend on residential fundamental amenities (b) and residential agglomeration economies that depend not only on its own residence density but also on the positive spillover effects from other street tracts' dense population (Ω) :

$$B_i = b_i \Omega_i^{\eta},\ \Omega_i \equiv \sum_{r=1}^{S} e^{-\rho\tau_{ir}}\left(\frac{H_{Rr}}{K_r}\right), \tag{16b}$$

where H_{Rr}/K_r is residential population density per unit of land area; residential spillover effects decline with travel time (τ_{ir}) through the iceberg factor $e^{-\rho\tau_{ir}} \in (0,1]$; ρ determines their rate of spatial decay; and η reflects the importance of residential agglomeration economies to residential amenities. The introduction of these agglomeration forces generates the potential for multiple equilibria of the model if they are sufficiently strong relative to the exogenous differences in characteristics across locations.

3.5 Endogenous public good provision

We incorporate endogenous public good provision. The city government collects the net rental income and then allocates it to different localities to provide public goods. The public goods improve local fundamental amenities a and b. Specifically, for each street tract i, we let

$$a_i = a_i^0 (g_{ai} S_a G)^{\tilde{\gamma}} \tag{17a}$$

and

$$b_i = b_i^0 (g_{bi} S_b G)^{\tilde{\gamma}} \tag{17b}$$

where a_i^0 and b_i^0 are the local natural and geographical conditions that influence local production and residential fundamental amenities, respectively; G is the rental income generated from the city's total floor space net of construction cost[21], which is all used to finance the city's public goods provision; S_a and S_b are shares of G that are used to provide public goods related to production amenities and residential amenities, respectively. For each street tract i, g_{ai} and g_{bi} are the shares of public expenditures this locality receives on improving its local production and residential amenities, respectively. And $\tilde{\gamma}$ is a parameter that measures the elasticity of local fundamental amenities w.r.t. public expenditure.[22] The overall value of G is endogenously determined as follows:

$$G = \sum_i^{I=209} (Q_i L_{Ri} + q_i L_{Mi}) - \sum_i^{I=209} cost_i(L_i, \varphi_i). \tag{18}$$

3.6 Commuting congestion

Next, we consider the congestion effect, the opposite force against agglomeration forces discussed in Section 3.4. Recall that Section 2 describes subways and automobiles as Shanghai's primary commute modes. Intuitively, a higher density of the residential population at the origin is more likely to generate traffic jams when so many people go to work from home during the rush hours in the morning. For example, the entrance from the local road to the highway/freeway would be crowded; the waiting line to get on the subway/or buses would be extended. A higher density of the working population at the destination is also more likely to cause congestion when so many people exit the main road or subway and head to the office at the same time. Moreover, the cross-traffic flow at the congested segments along the road network would slow the travel speed. A similar logic applies to the rush hours in the evening.

Therefore, we let τ_{ij}, the commuting time between street tracts i and j, depend on the origin's (street tract i) residential population density, denoted by H_{Ri}/K_i, the destination's (street tract j)

[21] Zero profits due to perfect competition among land developers imply that the housing rental income net of construction cost is equal to the land price. In reality, the city governments grasp the rental income through auctioning off the land for development.

[22] Following Henderson, Su, Zhang, and Zheng (2022), we set $\tilde{\gamma} = 0.06$.

employment density, denoted by H_{Mj}/K_j, and the cross-traffic flow, denoted by C_{ij}, in addition to the straight-line distance between the two locations, denoted by $dist_{ij}$, and the transportation infrastructure at both the origin and destination.[23] We specify the following model for the bilateral commuting time between street tracts i and j:

$$\log\tau_{ij} = t_0 + t_1 \log\left(\frac{H_{Ri}}{K_i}\right) + t_2 \log\left(\frac{H_{Mj}}{K_j}\right) + t_3 \log\left(C_{ij}\right) + \phi\left(dist_{ij}\right) + t_4 T_{Ri} + t_5 T_{Mj}, \tag{19}$$

where T_{Ri} and T_{Mj} capture the transport infrastructure, such as access to the subway, buses, and highways at the origin and working locations, respectively; and $\phi'(\cdot) > 0$. Importantly, $t_1 > 0$, $t_2 > 0$, and $t_3 > 0$, capturing the commuting congestion effects caused by high population densities at the residence and workplace, and cross-traffic flows along the travel route, respectively. Introducing these congestion forces mitigates the chances of multiple equilibria of the model.

3.7 Equilibrium

Let us define the parameter space of the model as $\Theta \equiv \{\alpha, \beta, \kappa, \varepsilon, H, \boldsymbol{a^0}(\boldsymbol{g_a S_a})^{\tilde{\gamma}}, \boldsymbol{b^0}(\boldsymbol{g_b S_b})^{\tilde{\gamma}}, \boldsymbol{K}, \boldsymbol{\varphi}, \boldsymbol{\theta}, \tilde{\gamma}, \lambda, \delta, \eta, \rho, t_1, t_2, t_3, \phi, \bar{c}, e_0, e_1, \overline{depth}\}$. Applying equations (5b), (7), (9), (11), (12), (14), (15a, b), 16(a, b), 17(a, b), (18), and (19) and remembering that for each street tract $H_R = \pi_R H$ and $H_M = \pi_M H$, we can solve for the equilibrium of the model which is described by the following set of endogenous variables $\{\boldsymbol{\pi_R}, \boldsymbol{\pi_M}, \boldsymbol{q}, \boldsymbol{Q}, \boldsymbol{w}, \boldsymbol{\xi^0}, E(U), G\}$. Because we have incorporated two opposite externalities in the model, positive agglomeration forces and negative congestion forces, under certain parameter spaces, the model may have a unique equilibrium solution (Allen and Arkolakis, 2022).

4. Data and Descriptive Patterns

This section describes various data sources and variable constructions utilized in our analysis. We also present some raw data patterns regarding Shanghai's internal urban structure.

4.1 Data and variable construction

We construct data for 209 street tracts in Shanghai. The data set includes each tract's residential and

[23] The form of the commuting costs between any two street tracts in our paper echoes the expression of the transportation costs between any two locations specified by Allen and Arkolakis (2022), which developed a quantitative GE model featuring endogenous transportation costs and traffic congestion and applied it to evaluate the welfare impact of transportation infrastructure. Their approach can yield the transportation costs between any two locations as a function of the underlying quality of infrastructure and the strength of traffic congestion.

workplace employment population, land price by use type, housing prices, land development densities, workplace wage, geological conditions, land use conditions, and local attributes. It also has each bilateral tract pair's commuting flow, commuting time, and pass-through traffic at bottlenecks in the road network. Below, we present detailed discussions.

4.1.1 Bilateral commuting flow and residential and workplace employment population

We construct the commuting flow between every pair of street tracts and each tract's residential and workplace employment using the 2015 Population Census data supplemented by a 2019 commute-flow dataset from a leading location service company.

The 2015 Population Census data we have is a 15-percent sample of the 2015 One-Percent Population Survey (also known as the 2015 mini Census). The survey contains questions on individuals' employment status, home address, and the street tract address of the workplace. Our sample contains 35,130 individuals who lived in Shanghai on October 31, 2015, and 16,092 individuals were working when the survey was conducted. We excluded 192 workers who reported their work locations outside of Shanghai. The remaining sample for our analysis contains 15,900 workers; all reported their street tracts of residence and workplace as well as their commuting times.

When computing the bilateral commuting flow between each pair of street tracts, we assign weights to each worker based on the ratio of the 2015 residential population of the district where the workers lived to the total number of individuals in our sample residing in that district. The specific 2015 population figures for Shanghai's districts are sourced from the Shanghai Bureau of Statistics. Refer to Table A1 in the appendix for the detailed district weights.

Note that among the 209*209 street-tract pairs, only 4,705 have non-zero commuters in our Census data.[24] To address the concern of the possible under-representation problem of commuters along certain bilateral routes, we obtained access to the complete commuting flow matrix between any two street tracts in Shanghai in November 2019 from one of China's leading companies that provide location services on mobile devices and use it to fill in the "blanks" in the Census.

The company collected each mobile device's location information to which it provides location services. The company identifies each device's typical daytime and nighttime locations based on its location tracks in the past three months. Chen et al. (2024) suggest that the data can present a good approximation of the actual commuting flows in China due to the broad coverage of the mobile applications of the company's location services and the high frequency of its location track records.

[24] The average bilateral commute distance is 14 km for those street tract pairs with non-zero commuters and 34 km for those pairs with zero commuters.

There are 8.3 million workers presented in its 2019 commuting flow data for Shanghai. Because Shanghai's actual employment population in 2019 was 13.76 million, according to the official statistics, the company's 2019 commuting flow data may still undercount the city's commuters/workers. We use this data as complementary data to fill in the number of commuters for the street tract pairs with zero commuters in the Census data.[25] The calculation details are presented in Appendix B. Additionally, using such an adjusted commute flow matrix, we then calculate each street tract's residential and workplace employment population.

4.1.2 Bilateral commuting time

We collected information on the shortest commuting times among all the traffic modes (i.e., cars, public transit, walking, and biking) between the centroids of any two street tracts from map.baidu.com, a leading provider of digital map and online navigation services in China. In particular, we scrambled the traveling time data at 8 am on December 2nd, ninth, and 16th of 2020, when the spread of COVID-19 was under control in Shanghai. The bilateral commuting time we use is the average of the shortest traveling times on the three Wednesday mornings. In particular, the data contains the bilateral commuting times for all the between-tract bilateral commute routes (209*208). Within-tract commute times are recorded as zero. The bilateral commuting times from the 2015 mini Census are available only for those street tract pairs with positive numbers of commuters (4,705 pairs). The correlation coefficient between the two sources is 0.5309. We use the bilateral commuting times from the Baidu map because of the concern about the errors in the self-reported commuting times in the Census and the missing commuting times for the routes with zero commuting flows.

4.1.3 Measuring the cross traffic for each bilateral commuting route

In Shanghai, over 80% of between-tract driving routes recommended by navigation APPs utilize elevated highways or controlled-access freeways. Although much congestion occurs at the entries and exits within this type of highway network, some bottleneck points in the network that potentially bring in large volumes of cross traffic may also slow down the driving speed and cause congestion for automobile riders. We geocode all the highways and freeways in Shanghai's transportation map as of 2015 (see Figure A1 in Appendix A). We then use ArcGIS to find the shortest route between any two street tracts' centroids along the highway network (see an example in Figure A2 in Appendix A) and denote this route as the bilateral commuting route. We pin down all the pass-through street tracts along

[25] We apply a scalar to the 2019 commuting matrix to address the concern for the under-coverage of the company's location services as well as the overall employment population growth between 2015 and 2019.

every bilateral commuting route. Next, we identify the bottleneck street tracts in the highway network. For each street tract, we calculate its frequency of being passed through by any bilateral commuting route in this highway network. We consider the street tracts passed through most frequently as the bottleneck street tracts because a large volume of cross traffic may be brought in around those street tracts. For the primary analysis, we designate the top 10% (21 street tracts) as bottlenecks (Figure A3 in Appendix A). Nearly 7,000 or more commuting routes pass through each of these bottlenecks. We cross-validate their locations with the traffic map indicating the driving speed by highway segment released by the official source (Figure A4 in Appendix A). We find that the bottleneck street tracts coincide with the highway segments that present the lowest driving speed in the traffic map, which suggests our definition of bottlenecks is plausible.[26]

The locations of bottleneck street tracts are determined solely by the highway infrastructure. However, how much cross traffic each bottleneck street tract can potentially bring in depends on the spatial distribution of the employment population. For each bottleneck b, we measure its potential pass-through traffic by aggregating the residence employment over all the 209 street tracts of Shanghai while weighting each street tract by its chance of having a bilateral commuting route (starting from itself) that passes through bottleneck b. Specifically, we define: $traffic_b = \sum_{i=1}^{209} \frac{N_{ib}}{209} \times H_{Ri}$, where N_{ib} represents the number of the bilateral commuting routes starting from street tract i and passing through bottleneck b, and H_{Ri} represents the residential employment population in street tract i.

Next, for each of the 209*208 bilateral commuting routes, we calculate the proxy for its cross-traffic by aggregating $traffic_b$ of all the bottlenecks located along this route. When the starting street tract is a bottleneck itself, we subtract its own residential employment from the aggregate sum. Specifically, the cross-traffic proxy of bilateral route ij is:

$$C_{ij} = \begin{cases} \sum_{b \in B(ij)} traffic_b, \ if\ i \notin B(ij) \\ \sum_{b \in B(ij)} traffic_b - HR_i, \ if\ i \in B(ij) \end{cases} \tag{20}$$

where $B(ij)$ represents the set of bottlenecks route ij passes through.

4.1.4 Computing land price by use type, housing development densities, and housing prices

We use land transaction information to compute each street tract's average prices of residential and business land (industrial and commercial, combined) and the price wedge between these two use types. Our land sample comprises all the land parcels sold through public auctions in Shanghai during 2007-2015. The land transaction data is obtained from the official website affiliated with China's Ministry of

[26] In the robustness checks, we slightly extend or trim the list of bottlenecks, and the estimates of congestion elasticities are robust.

National Land and Resources (landchina.com) and covers basic transaction information, such as land use type, lot size, sale price, sale date, and address. Moreover, the tract-level average residential housing price and building height (measured by FARs) are constructed from a residential-development-project-level data set sourced from the China Index Academy, a real estate think tank. Appendix C presents the data construction details.

4.1.5 Other data

Appendix C details other supplementary data used in our analysis. This includes information on the average wage, points of interests (POI) related to local amenities (from both the production and residential perspectives), land use conditions at the tract level, and the floor space stock of various uses at the district level.

4.2 Descriptive evidence

In 2015, Shanghai was home to 24 million residents and 11.3 million workers. In our study period, Shanghai had 16 urban districts, nine containing the core urban area ("core urban districts") and seven in the surrounding suburban area ("suburban districts").[27] The city center is in Huangpu District.

Figure 2 plots each street tract's residential employment density (Panel A), workplace employment density (Panel B), average building height measured by FAR (Panel C), and average housing price (Panel D) against the distance to the city center. Panels E and F of Figure 2 map the 209 street tracts in Shanghai according to their residential and workplace employment densities. While the spatial patterns presented in Panels A-D are consistent with the predictions of the monocentric city model, the spatial distributions of the residential and workplace employment densities are indeed quite asymmetric across space around the city center (Panels E and F). Relative to residential employment, workplace employment is more spatially concentrated in the city center, indicating separation of workplace from residence.

[Figure 2 about here]

Figure 3 plots the average commuting times, distances, and speeds of workers who live in each street tract against the tract's distance to the city center. Interestingly, the spatial patterns deviate from the typical commuting pattern of a monocentric city where residents who live further away from the city center would commute longer times than those who live nearer. By contrast, as shown in Figure 3, residents living in the 5-10 km belt commuted the longest times (Panel A) despite moderate commuting

[27] The seven suburban districts include Chongming, Baoshan, Jiading, Qingpu, Songjiang, Jinshan, and Fengxian.

distances (Panel B), indicating congestion. Although those who lived in the suburban districts traveled longer distances, most were not traveling to the central city for work (Panel B) and thus enjoyed a higher commuting speed.[28] Overall, the street tracts located 5-10 km away from the city center are the most congested areas in the city, as reflected by an average commuting speed lower than 20 km per hour shown in Panel C.

[Figure 3 about here]

Panel A of Figure 4 plots the bilateral commuting times adjusted for the effect of travel distance against the densities of employment population in both residence and workplace street tracts.[29] The two axes on the plane represent the employment densities of residential and workplace street tracts and the axis along the third dimension represents the adjusted travel time. Clearly, after conditioning out the effect of bilateral travel distances, travel times rise with both densities, highlighting the critical role of congestion arising from increased densities at the two ending points.

In addition, Panel B of Figure 4 presents the relationship between bilateral commuting times and the proxy of each bilateral route's cross-traffic flow, as constructed by Eqn. (20). We divide all the 209*208 between-tract bilateral routes into four categories based on the size of the cross-traffic flow along the respective bilateral route: 1 (light), 2 (moderate), 3 (crowded), and 4 (extremely crowded) as shown along the x-axis. The travel routes in these categories are 10,894, 10,844, 10,881, and 10,853, respectively. The y-axis represents the residual of bilateral commuting times from the regression of bilateral commuting time on travel distance, its squared term, and the fixed effects of residential and workplace street tracts (which take care of the ending point densities). Clearly, the residual commuting time monotonically increases with the cross-traffic flow proxy, underscoring the importance of considering the city's road network structure and spatial distribution of employment when measuring the congestion effects.

[Figure 4 about here]

Table 1-a reports the summary statistics of the key variables.

[28] In the 2015 Population Census sample, 8,047 workers lived in one of the seven suburban districts, 88.5% of whom also worked in a suburban district.

[29] The adjusted bilateral commute time is obtained by subtracting the nonlinear effect of bilateral travel distance from travel times. To estimate the effect of travel distance on travel time, we regress bilateral travel time on travel distance and its squared term, controlling for the fixed effects of residential and workplace street tracts. To help better visualize the relationships between bilateral commute times and the employment densities of residences and workplaces, Panel A of Figure 4 includes the street tract pairs with bilateral travel distances of 10 km or less (the average travel distance of the commuters in the Census sample is 10 km). The patterns are similar if we use other pairwise distance intervals.

[Table 1-a about here]

The 2015 Population Census provides data on the daily traffic modes used by commuters in Shanghai, including walking, biking, electric biking, motorcycles, cars, buses, subway, and others. Table 1-b presents the distribution of traffic modes for the entire sample and different subgroups based on commute distances. The usage of traffic modes varies significantly depending on commute distance. Among workers who commute within their residential street tracts (within-tract commuters), nearly 80% choose to walk or bike (including electric bikes) to work. In contrast, the proportion of workers commuting by walking and biking declines as the commute distance increases. Of those who commute 10 km or more, over 80% use subways, cars, or buses. As nearly 90% of the between-tract bilateral commuting routes are 10 km or longer, we consider subways and automobiles the primary traffic modes for our congestion estimation.

[Table 1-b about here]

5. Estimation

In this section, we estimate three sets of key parameters of the model. These parameters will be used later in the calibration and simulations of the model.

5.1. Gravity model estimation of semi-elasticity of commuting flows w.r.t. commuting time

We first estimate $\upsilon = \varepsilon\kappa$ using a bilateral commuting flow regression model that is derived from the gravity equation (5a) characterizing the probability that a worker chooses to live in street tract i and work in street tract j: $\log\pi_{ij} = -\upsilon\tau_{ij} + \vartheta_i + \varsigma_j$. Here, the residential fixed effects, $\vartheta_i \equiv \varepsilon logB_i - \varepsilon(1-\beta)logQ_i + const$, capture all characteristics of the origin residence that affect the commuting outflows; the workplace fixed effects, $\varsigma_j \equiv \varepsilon logw_j$, capture the workplace productivity that affects the commuting inflows; $-\upsilon\tau_{ij}$ absorbs the commuting frictions caused solely by bilateral commuting time between the origin and the destination. We use a stochastic error to capture the measurement error in travel time. The bilateral commuting flow regression specification thus is given by:

$$\log\pi_{ij} = -\upsilon t_{ij} + \vartheta_i + \varsigma_j + e_{ij}. \tag{21}$$

We use the constructed commuting flow data to compute the probability that a worker commutes between any of the 209 street tracts in Shanghai, which returns 209*209=43,681 pairs of bilateral commuting probabilities (π_{ij}). Of all the 209*209 bilateral routes, 93.6% (40,884 routes) have non-zero commuting flows. To allow for granularity and zeros in bilateral commuting flows (Dingel and Tintelnot, 2020), we estimate the commuting gravity Eqn. (21) using the Pseudo Poisson Maximum Likelihood (PPML) estimator of Santos Silva and Tenreyro (2006). In column (1) of Table 2, we estimate the gravity equation using PPML and find a semi-elasticity of -0.076, which is statistically significant. We also conducted PPML estimations that use various subsamples of the bilateral street tract pairs or allow for some specific region pairs to have different commute probabilities (see columns (2) and (3) of Table 2). Additionally, we use the commute flows of all the 16*16 bilateral district pairs to run the regression and report the estimate in column (4). Lastly, we use a control function approach to include the first-stage residuals in the PPML estimation to address the potential endogeneity of actual travel time (Atalay et al., 2019). [30] Following Koster (2024), we use the bilateral straight-line distance as an instrument, with the first-stage F-statistic at 31158. Column (5) reports the estimate. All the estimates of the semi-elasticity are quantitatively similar, which range from -0.075 to -0.087.[31]

[Table 2 about here]

5.2. Congestion effect

Next, we estimate the parameters in the bilateral commuting time Eqn. (19) using the commuting times for all the 209*208 between-tract bilateral commuting routes. Because information on within-tract commuting time is unavailable and most within-tract commuters walk or bike, we assume no congestion for within-tract commuting. Based on the discussions in Sections 2.2 and 4.2, we are particularly interested in the three congestion effect coefficients associated with the residential employment density at the original location ($empden_{Ri}$), the workplace employment density at the destination location ($empden_{Mj}$), and the cross-traffic flow along the bilateral route (C_{ij}) as defined in Eqn. (20). The regression specification is (22a):

$$log\tau_{ij} = t_0 + t_1 logempden_{Ri} + t_2 logempden_{Mj} + t_3 logC_{ij} + \phi_1 logdist_{ij} + t_4 T_{Ri} + t_5 T_{Mj} + u_{ij} \quad (22a)$$

Here, t_1, t_2, and t_3 are the parameters of interest, which are expected to be positive; T_{Ri} and T_{Mj} are the transport infrastructure variables of residence street tract i and workplace street tract j, including the

[30] Actual travel times are endogenous for several reasons. First, travel times are longer along bilateral routes where there are many commuters, leading to a positive bias in the estimate. Second, the routes with large commuting flows likely have better transportation infrastructure, which could lower travel times, leading to a negative bias in the estimate. Lastly, travel times may be measured with errors.

[31] As a further check on the semi-elasticity functional form, we regress both the log bilateral commuting probabilities and commute times (at the street-pair level and district-pair level) on the residence and workplace fixed effects and plot the respective residuals from these two regressions against one another. Figure A5 in Appendix A shows an approximately linear relationship between these two residuals, which suggests that the semi-elasticity functional form provides a good fit to the data.

densities of parking lots, train stations, airports, docks, subway stops, bus stops, and road infrastructure (elevated highways, bridges, flyovers, and tunnels) of the origin and destination tracts (all in logs).

When estimating t_1 (the congestion effect of the residential employment density), we include the fixed effects of workplace street tracts to absorb all the effects of the factors associated with the destination location on the bilateral travel times. In particular, we rewrite the regression model (22a) as follows:

$$log\tau_{ij} = t_1 logempden_{Ri} + t_3 logC_{ij} + \phi_1 logdist_{ij} + t_4 T_{Ri} + FE_{Mj} + u_{ij}, \quad (22b)$$

where FE_{Mj} represents the fixed effects of workplace street tracts, which fully absorb $(t_0 + t_2 logempden_{Mj} + t_5 T_{Mj})$ in Eqn. (22a); conditioning on the workplace street, the variation that identifies t_1 comes from the variation in the residential employment density across different residence street tracts. Similarly, when estimating t_2 (the congestion effect of the workplace employment density), we include the fixed effects of residence street tracts to absorb all the effects of the factors associated with original place.

An identification problem is that employment densities are endogenous to local accessibility (e.g., transport connections). For example, those locations with better transport connections are more attractive to commuters and firms, thereby having higher residence/workplace employment densities. Omitting the unobserved characteristics related to local accessibility would cause a downward bias in the OLS estimation (or a negative bias). To address the problem, we instrument each street tract's employment densities with the log of the straight-line distance between the street tract's centroid and Shanghai's city center. As shown in Figure 2, employment densities are highest in the locations near the city center and decline as one moves away from it. The identification assumption is that the unobserved factors correlated with travel times are uncorrelated with the origin (or destination) tract's distance from the city center, conditioning on all the controls, including the log of the bilateral travel distance, the transport infrastructure, and the destination (or origin) street tract fixed effects. In addition, we assume that the cross-traffic flow (C_{ij}) is independent of these unobserved factors in the error term. We consider this assumption valid because C_{ij} is determined by the spatial organization of the highway network and employment, rather than any factors specific to the starting or ending points of route ij.

We report the OLS results in columns (1) and (2) of Table 3. In columns (3) and (4), we report the IV estimates. As expected, the IV estimates are larger than the OLS estimates regarding magnitudes. The first-stage F-statistics are far larger than 10, suggesting that the distance to the city center is a powerful instrument. According to the IV estimates reported in columns (3) and (4), on average, a 100% increase in the employment density at the residence place (or workplace) will increase bilateral travel times by about 21%. The elasticity of commuting times w.r.t. the cross-traffic flow (t_3) is estimated to be around 0.007. The coefficients on the log of the bilateral travel distance are around 0.7, which suggests that the commute speed increases over longer travel distances.[32]

[Table 3 about here]

To check the robustness of the estimates of the coefficients on the route-specific variables, $logC_{ij}$ and $logdist_{ij}$, we run an OLS regression according to specification (22a) while including the fixed effects of both the residential and workplace street tracts. Column (5) reports the results, which show that the estimated coefficients on these route-specific variables are similar to those reported in columns (3) and (4).

5.3 Estimating and calibrating the parameters defining unit construction cost function

We now estimate the parameters in the unit construction function, $c_i(\varphi_i) = \bar{c} \times {\varphi_i}^{e0+e1\times|depth_i-\overline{depth}|}$, as specified by Eqn. (13b) in Section 3. According to Ahlfeldt (2023), the elasticity of the construction cost w.r.t. building height φ_i increases with bedrock depth if the bedrock depth is deeper than 35 meters under the ground. Thus, we let $\overline{depth}$=35. In Shanghai (excluding Chongming Island), across street tracts, the bedrock depth ranges from 85 to 187 meters with an average of 130 meters, much deeper than 35 meters.

For the estimation, we collect a sample of residential land parcels with detailed land transaction information, geological information (e.g., bedrock depth), and *ex-post* housing development information (e.g., FAR and per floor space housing price) in the vicinity of the land parcel. For each land, the *ex-post* building height and price are calculated as the average FARs and prices of all residential developments within a 1.5 km ring area around the land, respectively.[33] The land parcels were all sold through public auction. Considering that the land sales revenue of each land parcel equals the value of the house built on the land, subtracting the construction costs, we calculate the unit construction cost as follows: $c(\varphi) = \frac{Q\times\varphi\times K - pr\times K}{\varphi\times K}$, where φ is the building height, Q is the unit housing price, K is the land parcel area, and pr is the unit land price.

Using this variable as the outcome, we specify the following regression model to estimate e_0 and e_1:

$$logc_l(\varphi_l) = cons + e_0 log\varphi_l + e_1 log\varphi_l \times (depth_l - 35) + error_l, \qquad (23)$$

[32] The results remain similar when including the squared term of the log bilateral travel distance.

[33] We restrict the regression sample to those within 30 km of the city center of Shanghai, considering that 90% of the residential developments in our sample are located within this area. Additionally, we exclude a few land parcels located in the street tracts with an extremely deep bedrock depth (i.e., more than 160 meters). Table A3 in Appendix A reports the summary statistics.

where the explained variable is the log of the thus-computed unit construction cost of land parcel l; φ_l is the building height on the land parcel (measured by the average FAR of the *ex-post* housing developments); $depth_l$ is the average bedrock depth of the street tract where the land parcel is located; and $error_l$ is an error term.

Following the literature (e.g., Ahlfeldt and McMillen, 2018; Ahlfeldt et al., 2023), we use distance from the city center as the instrumental variable for the building height measure because it affects building height via the demand side and, hence, helps alleviate the confounding effects of supply-side factors (e.g., ruggedness) that could directly affect construction cost and building height. Furthermore, the instrument helps mitigate the endogeneity problem arising from a measurement error in our building height measure.

Table 4 reports the estimation results. While all the estimates of e_0 are positive and significant, those of e_1 are mostly small and insignificant. The magnitudes of the IV estimates exceed those of the OLS. The findings indicate that the building height elasticity of construction cost is approximately 1.29, as reported in column (3), higher than the average height elasticity of 1.01 for East Asia and Pacific cities, as documented by Ahlfeldt et al. (2023). Apart from the difference between building density and height, this notable difference in elasticity can be attributed to the unique geological conditions present in Shanghai. Situated within the alluvial plain of the Yangtze River Delta, historically, Shanghai was formed by sediment deposition. The bedrock in most of Shanghai lies deeper than 100 meters and is covered by loose soil and alluvial sand. These loose soil and sand cannot provide sufficient natural foundations, thus necessitating costly ground treatment and stabilization measures before constructing buildings. As a result, the construction cost increases more significantly with height than in many other Asian cities. Column (4) demonstrates that the height elasticity of construction cost does not notably escalate with the depth of bedrock. This is possibly because the bedrock throughout Shanghai is too deep to reach for building ground foundations, which has forced developers to adopt new construction techniques tailored to accommodate Shanghai's unique geological conditions.

[Table 4 about here]

We then calibrate the value of $\bar{c}$ such that the predicted total net house income matches the actual total land sale revenues of the whole city. We obtain $\bar{c} = 204$. We also conduct robustness checks by trying different values of these cost parameters in the counterfactual analysis and the results are qualitatively similar.

6. Calibration

In this section, we discuss in detail the calibration of the four sets of key model parameters. Based on the calibrated parameters, we conduct various over-identification checks of our model.

6.1. Calibration of key parameters

We shall calibrate four sets of parameters: (i) κ, the semi-elasticity of bilateral commuting cost w.r.t. commuting time; and ε, the dispersion of workers' idiosyncratic preferences towards any residence-workplace pair; (ii) the production and residential amenities of each street, A and B; and the corresponding local fundamental amenities a and b; (iii) the supply of overall floor space in each street tract, L, and the share of residential floor space in each street tract, θ; (iv) the exogenous local fundamentals $\bar{a}$ and $\bar{b}$ after isolating the impact of endogenous public goods.

6.1.1 Calibrating $\boldsymbol{\varepsilon}$ and $\boldsymbol{\kappa}$

In Section 5.1, we have estimated the coefficient that captures the responsiveness of bilateral commuting flow w.r.t. the bilateral commuting time, υ. This coefficient is the product of two parameters: κ, the semi-elasticity of bilateral commuting cost w.r.t. commuting time (see Eqn. (2)); and ε, the shape parameter of workers' idiosyncratic preference towards any residence-workplace pair. We shall next calibrate the above two parameters from υ.

We follow Ahlfeldt et al. (2015) to calibrate ε from wage data. First, we calculate the transformed wage for each workplace street tract from Eqn. (7). Specifically, we define the transformed wage for workplace street tract j as:

$$\omega_j \equiv w_j^{\varepsilon}.$$

Plugging the above definition and Eqn. (2) into Eqn. (7), we obtain

$$H_{Mj} = \sum_{i=1}^{S} \frac{(\omega_j / e^{\varepsilon\kappa\tau_{ij}})}{\sum_{s=1}^{S}(\omega_s / e^{\varepsilon\kappa\tau_{is}})} H_{Ri} \, , j = 1, \dots, S.$$

With the estimate of $\upsilon = \varepsilon\kappa$ and the data on $\{\tau_{ij}\}$ (bilateral travel time), $\{H_{Mj}\}$ (workplace employment), and $\{H_{Ri}\}$ (residence employment), we can solve for the transformed wages ω_j, $j = 1, \dots, S$.

We next calculate the variance of the log of transformed wage across street tracts ($\mathrm{var}(\log\omega_j)$). We use each one-digit industry's average wage in Shanghai as of 2015 obtained from tjj.sh.gov.cn, multiplied by this industry's employment share in each street tract obtained from the Economic Census 2008, to calculate the tract's average wage $\widehat{w_j}$ as proxy for w_j up to certain scale. Then we calculate the variance of the log of average wage $\mathrm{var}(\log w_j) = \mathrm{var}(\log\widehat{w_j})$ across street tracts. Because $\omega_j = w_j^{\varepsilon}$, we have

$$var(log w_j) = \frac{1}{\varepsilon^2} var(log \omega_j).$$

We can then obtain $\varepsilon = 8.4486$ from the above equation. Note that the value of this dispersion parameter in the previous literature is 6.83 in Berlin (Ahlfeldt et al., 2015) and 5.25 in London (Heblich et al., 2020) in the 19th century and 8.3 in Dhaka in 2009 (Kreindler and Miyauchi, 2023). Based on the values of υ and ε, we obtain $\kappa = \frac{\upsilon}{\varepsilon} = 0.0088$, close to the values in Tsivanidis (2024) and Ahlfeldt et al. (2015), which are 0.011 and 0.01, respectively.

As a robustness check, we employ an alternative approach to estimate κ. Specifically, we estimate κ based on a commute mode choice model, using commuter-level data from the 2015 mini Census, matched with mode-specific travel times for bilateral commute routes obtained from map.baidu.com. We obtain an estimate of κ to be 0.0094. Based on this estimated κ and the previously estimated υ, we obtain $\varepsilon = \frac{\upsilon}{\kappa} = 7.9093$. Both κ and ε, obtained through this method, are close to our previous estimates of 0.0088 and 8.4486, respectively. The estimation details are presented in Appendix D. These calibrated parameters and those borrowed from the literature are reported in Table 5.

[Table 5 about here]

6.1.2 Calibrating the values of residential and production amenities

First, we calculate the residential amenities B_i, $i = 1, \ldots, S$. Since locational equilibrium implies that the expected utility anywhere in the city should be the same, we normalize the equilibrium utility level specified in Eqn. (9) corresponding to the benchmark case to be one. Therefore, the overall probability of a worker residing in street tract i, π_{Ri}, as specified in Eqn. (5b), can be re-written as

$$\frac{H_{Ri}}{H} = \pi_{Ri} = \frac{(B_i Q_i^{\beta-1})^{\varepsilon} \sum_{j=1}^{S} (w_j/d_{ij})^{\varepsilon}}{(1/\gamma)^{\varepsilon}}.$$

Rearrange it, we have

$$\frac{H_{Ri}}{H}\left(\frac{1}{\gamma}\right)^{\varepsilon} = (B_i Q_i^{\beta-1})^{\varepsilon} \sum_{j=1}^{S} (w_j/d_{ij})^{\varepsilon} = B_i^{\varepsilon} Q_i^{-\varepsilon(1-\beta)} W_i,$$

where $W_i \equiv \sum_{j=1}^{S}(w_j^{\varepsilon} d_{ij}^{-\varepsilon}) = \sum_{j=1}^{S} \omega_j e^{-\kappa\varepsilon\tau_{ij}}$, which is the commuting market access of residence street tract i. This implies that

$$\log B_i = \frac{1}{\varepsilon} log H_{Ri} + (1-\beta) log Q_i - \frac{1}{\varepsilon} log W_i - \frac{1}{\varepsilon} log H - log\gamma. \quad (24a)$$

Intuitively, high residential employment and high floor prices must be explained either by high commuting market access (W) or by attractive residential amenities (B). Based on Eqn. (24a), we apply the calibrated ε, κ, and $\{\omega\}$ and use data on residential housing price per floor space Q_i, bilateral commuting time matrix, and residential employment in each street tract H_{Ri} to calculate B_i. We borrow $(1-\beta)$ (the share of consumer expenditure on residential floor space) from the literature based on some Chinese Household survey, which is around 0.3 (Cao et al., 2018).

Next, we calculate the production amenities A_j, $j = 1, \dots, S$. According to Eqn. (11) and considering $w_j = \omega_j^{1/\varepsilon}$, we have

$$q_j = (1-\alpha)\left(\frac{\alpha}{w_j}\right)^{\alpha(1-\alpha)}\left(A_j\right)^{\frac{1}{1-\alpha}} = (1-\alpha)\alpha^{\alpha/(1-\alpha)}(\omega_j)^{-\frac{\alpha/(1-\alpha)}{\varepsilon}}\left(A_j\right)^{\frac{1}{1-\alpha}}.$$

This implies that

$$logA_j = \frac{\alpha}{\varepsilon}log\omega_j + (1-\alpha)logq_j - \log\left((1-\alpha)\alpha^{\alpha/(1-\alpha)}\right). \tag{24b}$$

Notice that in our data, all the street tracts of Shanghai have positive residential and workplace employment. Therefore, according to Eqn. (14), we can calculate $q_j = \frac{\xi_j^0 + c_j(\varphi_j) * \varphi_j / pr_j}{1 + c_j(\varphi_j) * \varphi_j / pr_j} Q_j$, using the price wedge between business and residential land ξ_j^0 and the price per unit of residential land pr_j computed in Section 4.1.4, the unit construction cost $c_j(\varphi_j)$ predicted in Section 5.3, and data on the unit residential floor space price Q_j and the building height φ_j. We then apply the calibrated ε, κ, $\{\omega\}$ and $\{q\}$ to Eqn. (24b) to calculate A_j. We borrow the share of business floor space in production $(1-\alpha)$ and the share of land in housing production $(1-\mu)$ from the literature (Valentinyi and Herrendorf, 2008; Tan et al., 2020; Henderson et al., 2022), as shown in Table 5.

After calibrating A and B for each street, we next decompose A and B into 1) the local fundamental amenities determined purely by local natural conditions and local public goods; and 2) the agglomeration forces following Ahlfeldt et al. (2015). Specifically, as discussed in the model section, the productivity amenity of street tract i depends on production fundamental amenities (a) and externalities arising from employment agglomeration (Y):

$$A_i = a_i Y_i^{\lambda}, Y_i \equiv \sum_{s=1}^{S} e^{-\delta\tau_{is}}\left(\frac{H_{Ms}}{K_s}\right).$$

The residential amenities of street tract i depend on residential fundamental amenities (b) and externalities generated by residential agglomeration (Ω):

$$B_i = b_i \Omega_i^{\eta}, \Omega_i \equiv \sum_{r=1}^{S} e^{-\rho\tau_{ir}}\left(\frac{H_{Rr}}{K_r}\right).$$

Using data on (H_{Ms}/K_s), (H_{Rr}/K_r), bilateral commute time $\{\tau_{ij}\}$ and borrowing agglomeration parameters λ, δ, η, and ρ from Ahlfeldt et. al (2015), as shown in Table 5, we can back out a and b for each street tract.

6.1.3 Calibrating the street-tract-level floor space supply, the share of residential floor space, and construction land supply

We calibrate each street tract's residential floor space supply and business floor space supply according to equations (15a) and (15b). Essentially, if the economy is in equilibrium, housing market clearance would imply equality between housing demand and housing supply. We thus can back out the floor space supply for each tract by land use type using the demand side information. Then, we sum up the residential floor space supply and business floor space supply to get the total floor space supply for each tract. Dividing each tract's residential floor space supply by its total supply, we thus obtain the calibrated share of residential floor space, θ. This is also the share of residential land since the building height is the same for different land use types. Dividing each street tract's floor space supply by its building height, we can obtain its construction land supply.

As an over-identification check, we cross-check the validity of the calibrated floor space supply by aggregating it to the district level and comparing the thus-obtained district-level floor supply with the actual district-level floor space reported by the Shanghai Statistical Yearbook 2016 for each use type. The correlation coefficients are 0.88, 0.92, and 0.80 for the total, business, and residential floor space, respectively. See Figure 5.

[Figure 5 about here]

6.1.4. Calibrating the exogenous part of local fundamental amenities

This section calibrates the exogenous part of local fundamental amenities by isolating the impact of public goods endogenous to land sale revenues. First, we calculate the difference between the floor space rental income and the construction costs by use type for each street tract. By aggregating it across use types and tracts, we obtain the calibrated total land sales revenues, *G*, which are used to provide public goods, assuming all the net house rental incomes are captured by the city government through land sales revenues (see Eqn. (18)).

Remember equations (17a) and (17b) that define $a_i = a_i^0(g_{ai}S_aG)^{\tilde{\gamma}}$ and $b_i = b_i^0(g_{bi}S_bG)^{\tilde{\gamma}}$. We then apply the previously calibrated G, a, and b to equations (17a) and (17b) and obtain the values of $\overline{a_i} \equiv a_i^0(g_{ai}S_a)^{\tilde{\gamma}}$ and $\overline{b_i} \equiv b_i^0(g_{bi}S_b)^{\tilde{\gamma}}$. These are the exogenous factors that determine the local fundamental production and residential amenities, respectively. They reflect the local natural and geographical conditions, in addition to the city government's preference towards each locality in allocating public resources to provide public infrastructure and services. As such, $\bar{a}$ and $\bar{b}$ will serve as the loading factors to calculate the new values of local fundamental amenities after being multiplied by an overall public goods expenditure in our simulations later. For a bit of abuse of terminology, from now on, we refer to $\bar{a}$ and $\bar{b}$ as local fundamentals.

Are these calibrated local fundamentals sensible? As an over-identification check, we run separate regressions of $\bar{a}$ and $\bar{b}$ (in logs) on a battery of observed street-tract-level characteristics that potentially affect local suitability for production or residence. As shown in column (1) of Table 6, local production fundamental, $\bar{a}$, is significantly and positively correlated with local transport connections measured by the densities of train stations, airports, docks, and subway stops. Column (2) shows that a street tract's residential fundamental, $\bar{b}$, increases with the density of general hospitals but decreases with the densities of specialized hospitals, emergency medical centers, and disease control and prevention centers. Green space share (forest and grass combined) is found to be positively associated with the value of residential fundamentals.

[Table 6 about here]

Panels A and B of Figure 6 show the spatial distributions of $\bar{a}$ and $\bar{b}$ (in logs) throughout Shanghai. Panel A shows that the street tracts with the highest value of production fundamentals are concentrated within the 5−20 km wide belt, containing almost all subcenter street tracts (represented by the polygons with black boundaries) and a few core-urban street tracts (represented by the polygons with golden boundaries). The values of production fundamentals are especially remarkable in the three subcenter tracts in Pudong District: *Hua Mu*, *Zhang Jiang*, and *Chuan Sha*. By contrast, Panel B shows that the street tracts near the city center have relatively low $\bar{b}$, and those with the highest $\bar{b}$ are within the 15-30 km wide belt. Several tracts in the edge towns (represented by the polygons with blue boundaries) also have high residential fundamentals. Notably, although several tracts in Chongming Island have relatively high values of residential fundamental amenities, land there is primarily restricted for non-urban development (e.g., agricultural areas, forests, and wetland reserves). Furthermore, Panel C shows the spatial distribution of $log(\bar{b}) - log(\bar{a})$, which indicates each street tract's fundamental comparative advantage in developing residential houses. While generally increasing with distance from the city center, these advantages vary among street tracts at equivalent distances, underscoring the asymmetric nature of fundamental amenity distribution across the city.

[Figure 6 about here]

6.2. Additional over-identification checks

We can use the calibrated street-tract-level floor space supply by use type, the residential and production fundamentals, and the other estimated model parameters to solve the model's equilibrium. As another over-identification check, we use our model to predict the equilibrium bilateral commuting flow probabilities for all the street tract pairs and then compare the model-predicted ones with the actual ones in the data. In Panel A of Figure 7, we show a scatterplot of the model's predicted bilateral commuting probabilities against those in the actual data for all the pairs of street tracts. Our model predictions fit the data well even at this disaggregated spatial scale (the correlation coefficient is

0.9131). Panel B shows the cumulative distribution function of commuters across the travel time bins in the model (the dashed red line) approximates that in the actual data (the solid black line) well.

[Figure 7 about here]

7. Counterfactual Analysis: Zoning Restrictions on Land Use Types, Building Height Constraints, and Market Demand

In this section, we first present basic patterns regarding the alignment between the current floor space supply and market demand across various localities within Shanghai. This analysis illuminates the spatial misallocation resulting from two important land use regulations: zoning on land use types and building height constraints. Subsequently, we delve into two counterfactual exercises. The first scenario allows market forces to determine the land allocation between residential and business uses within each street tract. The second scenario goes a step further. Besides relaxing the zoning restrictions on land use types, we also lift restrictions on building heights. This gives developers the freedom to set heights based on market signals and construction costs. It is important to note that the land development area (i.e., the construction land supply) in each street tract will remain constant at current levels for both counterfactual scenarios.

7.1 Misallocation of land between different use types and local comparative advantage

This subsection shows that, due to zoning, there is a misallocation between residential and business land use within each street tract. As shown in Figure 8, Panel B, each street tract's residential floor space share does not correlate with its local comparative advantage in residential amenities compared to business amenities. The results reported in column (2) of Table 7a confirm no statistically significant relationship between the residential floor space share and the local residential comparative advantage. This observation contradicts what one would expect from a market-oriented land allocation, where competitive bidding would have aligned the floor space share by use type with the local comparative advantage.

[Figure 8 about here]

[Table 7a about here]

The ratio of business land price to residential land price also reveals the extent of the government's manipulation of land allocation between these two use types (Henderson et al., 2022). Based on our data, business land prices are lower than residential land prices in 138 of Shanghai's 209 street tracts, with the average ratio of business to residential land price being 0.487. Furthermore, both Figure 8, Panel A, and Table 7a, column (1), demonstrate that the price wedge between business and residential land within each tract decreases as the tract's comparative advantage shifts towards residential amenities (i.e., as $log(\bar{b}) - log(\bar{a})$ increases). This finding suggests that the government underprices business land in areas with undesirable production amenities but desirable residential amenities by over-allocating business land there. This situation could result in inefficiency in land use.

7.2 Misallocation of floor space supply across different street tracts and local fundamentals

We next examine how each tract's overall floor space supply, under current land regulations, aligns with market demand driven by local fundamental amenities. Column (1) of Table 7b shows that after controlling for land area, there is no significant correlation between each street tract's overall floor space supply and the value of its production fundamentals, $\log(\bar{a})$. Moreover, each street tract's overall floor space supply is even negatively related to the value of its residential fundamentals, $\log(\bar{b})$. This negative correlation is likely due to the absence of urban construction on Chongming Island with desirable residential amenities. After excluding the tracts in Chongming from the regression sample, the correlation between floor space supply and residential fundamentals turns positive but statistically insignificant, as reported in column (2) of Table 7b. These findings indicate a great potential to improve the alignment between the floor space supply and the market demand driven by local fundamentals across different street tracts in Shanghai.

[Table 7b about here]

7.3 Counterfactual C1: Relaxing zoning restrictions on land use types

We now move on to our counterfactual analysis. First, for each street tract, we relax the zoning restrictions and allow the market to determine the land allocation between business and residential use. The land development area and building height in each street tract are kept unchanged. We refer to this counterfactual as *Counterfactual C1*. In equilibrium, the free arbitrage between different land uses would eliminate any price wedge between business and residential floor space. As a result, more floor space should be provided for residential use in street tracts with a higher comparative advantage in residential development. This is contrary to the current situation, where government intervention distorts the market, as shown in section 7.1.

To verify how the reform of *Counterfactual C1* helps correct such misallocation, we run a regression of each street tract's share of floor space for residential use on the tract's comparative advantage in residence over production, as indicated by $log(\bar{b}) - log(\bar{a})$. The results in Table 7a show that the positive correlation between each street tract's residential comparative advantage and its residential floor space share is significantly strengthened in *Counterfactual C1* (column (3)) compared to the initial case (column (2)). The R-squared value is also much larger than in the initial case.

The reallocation of land between different uses reshapes the spatial distribution of economic activities such as residential and workplace employment. Panels A (and D) in Figure 9 illustrate the residential (and workplace) employment densities for the initial benchmark case, while Panels B (and E) show these densities for *Counterfactual C1*. We observe that residential employment departs from core urban street tracts with a high comparative advantage in production and agglomerating in certain street tracts outside the core urban area with superior residential amenities compared to production amenities. Simultaneously, jobs flow to places more suitable for production, causing workplace employment to become more concentrated in the core area and several bordering street tracts.

Consistently, columns (1) and (3) in Table 7c show that each street tract's residential employment growth relative to the benchmark level in *Counterfactual C1* is positively associated with the local comparative advantage in residence over production and negatively associated with the local production fundamentals. Conversely, workplace employment growth in *Counterfactual C1* is higher for street tracts with superior production fundamentals but lower for street tracts with a higher local comparative advantage in residence, as indicated by the results reported in columns (2) and (4) of Table 7c.

[Figure 9 about here]

[Table 7c about here]

Overall, the welfare gain relative to the benchmark level is 6.7%, as shown in Table 8, column (1). This parallels the findings of Henderson et al. (2022) at the city level, demonstrating that eliminating favoritism towards business use in land allocation can enhance welfare by 8.1%. Table 8 also presents other key equilibrium outcomes that help us understand the forces driving the overall change in welfare levels. Notably, both the average wage and residential amenities increase (see Table 8, columns (2) and (6), respectively). This is because the land allocation between uses for each street tract now adheres to market signals, thus aligning better with the local comparative advantage. This alignment facilitates the agglomeration economies of both production and residence. As the oversupply of business land in locations with higher residential amenities has been addressed, housing prices, on average, have declined (see Table 8, column (3)).

We note that the increased concentration of residential or workplace employment in certain areas of the city results in heightened commuting congestion in these places. The separation of residential and workplace locations due to the departure of residents from the core urban area also extends the average commuting distance, as indicated in column (5) of Table 8. As a result, we observe an increase in average commuting time, as outlined in column (4) of Table 8. However, these negative effects of the reform are outweighed by the positive outcomes discussed earlier. Thus, the overall welfare gains are positive.

[Table 8 about here]

7.4 Counterfactual C2: Lifting the building height constraints

In our next counterfactual exercise, in addition to allowing free arbitrage of land between different use types, as in section 7.3, we further lift the building height constraints and let the developers set the building heights to maximize the value per unit of land considering market price signals and construction costs. Specifically, consider a representative developer in locality i. Suppose that this developer chooses building height in order to maximize the profits made from each unit of land (DiPascal and Wheaton, 1990). The developer's objective function is as follows

$$Max_{\varphi_i} Q_i \times \varphi_i - \varphi_i \times \bar{c} \times \varphi_i^{ec_i}$$

where φ_i is the building height, Q_i is the housing price, and ec_i is the elasticity of unit construction cost w.r.t. the building height. The optimal building height can be solved as $\varphi_i = \left(\frac{Q_i}{\bar{c}(1+ec_i)}\right)^{\frac{1}{ec_i}}$.

In *Counterfactual C2*, we maintain the land area allowed for development in each tract fixed at the initial level. The initial area is calculated as the initial floor space supply divided by the initial building height (i.e., the tract's average FAR). It varies by tract and is typically determined by the land development quota granted by the government to each street tract in accordance with the city's long-term plan. The average share of such land supply in the overall available land is 0.2 across street tracts. In other words, *C2* would lead to redistribution of floor space supply across different localities of the city because of letting the developers set building heights following market signals on the initially given amount of land.[34]

Through *Counterfactual C2*, the correlations between each street tract's overall floor space supply and its local fundamental production, as well as residence amenities, have both become significantly positive (see Table 7b, column (3)). This is a stark contrast to the initial case (see Table 7b, column (2)). This suggests that adhering to market signals can help mitigate the misallocation previously discussed in Section 7.2 and facilitate a more rational allocation of floor space across different tracts through developers' optimization of building heights. Furthermore, the correlation between each tract's residential floor space share and its local comparative advantage in residence remains fairly similar to

[34] In *Counterfactual C2*, we exclude one district, Chongming Island, and leave its current floor space supply unchanged. The main reason is as an island separated from the mainland of Shanghai, Chongming Island is designated as an ecological reservation area. Therefore, any large-scale land development is unlikely in the foreseeable future. In addition, Chongming's geological conditions are exceptional. Its bedrock depth is more than 480 meters under the ground, which makes constructing high buildings very costly.

the case of *Counterfactual C1* (see Table 7a, column (5)).

The redistribution of floor space leads to a spatial redistribution of residential and workplace employment. In *Counterfactual C2*, workplace employment has become more concentrated in the city core and several surrounding tracts and subcenter tracts with higher production fundamentals, compared to the case of *Counterfactual C1*, as depicted in Panels E and F of Figure 9. We also run a regression of each street tract's growth rate in workplace employment relative to the benchmark level in *Counterfactual C2* on its production fundamentals and local residential comparative advantage. The results are presented in Table 7c, column (6). Street tracts with stronger production fundamentals experience significantly higher workplace employment growth. In contrast, there is a negative correlation between the local comparative advantage in residence and workplace employment growth. These two correlations are significantly stronger than in the case of *Counterfactual C1*, as reflected by much larger coefficients and much higher R-squared (see columns (4) and (6) in Table 7c).

The growth of residential employment (relative to the benchmark level) in *Counterfactual C2* is negatively correlated with local production fundamentals but positively correlated with the local comparative advantage in residence over production. However, these two correlations have become weaker compared to the case of *Counterfactual C1* (see Table 7c, columns (3) and (5)). This could be because in some localities with high production fundamentals, such as certain core urban streets, high floor space prices have incentivized developers to increase building heights to augment the overall floor space supply. This increase could accommodate more business firms and residential dwellings simultaneously (see Panel C of Figure 9). Although these core urban streets have a low comparative advantage in residence (see Panel C of Figure 6), people may still choose to live there due to the proximity to workplaces.

Table 8 presents the equilibrium outcomes of *Counterfactual C2*. Due to the strengthened agglomeration economies of production, the wage rate significantly increases (see Table 8, column (2)), compared to *Counterfactual C1*. Moreover, as more floor space is built in localities with higher fundamentals, residential agglomeration also increases, thereby enhancing living amenities on average (see Table 8, column (6)). The average commuting distance is reduced compared to *Counterfactual C1*, suggesting that a floor space supply that responds to market demand helps workers live closer to their workplaces, reducing the separation between their residences and job locations. However, the average commuting time does not decrease, possibly due to increased congestion that counteracts the effect of the reduced commuting distance. The average housing price sees a slight increase compared to *Counterfactual C1* (see Table 8, column (3)), possibly due to the reduced total floor space supply and/or increased housing demand.[35] Nevertheless, the positive effects on welfare from increased wage rates and living amenities outweigh the impact of the housing cost increase. This results in an additional welfare gain of 2.4% on top of the gain from *Counterfactual C1*. It echoes Ahlfeldt et al. (2023), which show an estimated welfare gain of 3.1% from relaxing existing height constraints on skyscrapers in developing economies. Compared to the initial benchmark level, the overall welfare gain through *Counterfactual C2* is 9.1%.

The results above suggest that incorporating local fundamental conditions into zoning regulations and building height restrictions could improve the efficiency of floor space allocation across different uses and locations. Inspired by this idea, we thus explore the welfare consequences of setting regulations by establishing functional relationships between each tract's floor space supply (either overall or by use type) and its local fundamental amenities. We find that welfare could be improved by 2.4% to 6.3% compared to the benchmark, but smaller than the welfare gains in the scenarios where planners let the market forces determine how much and what to build. Refer to Appendix E for more details.

It is important to note that in all the counterfactual analyses presented in Section 7, we did not factor in demolition costs when calculating the welfare gains from various reforms. Consequently, the welfare gains we have calculated could be interpreted as potential bounds of welfare losses caused by the misallocation due to zoning restrictions and building height constraints.

8. Counterfactual Analysis: Spatial Development of Shanghai in the Future

Planning future spatial development is of significant importance for a metropolis like Shanghai, which urgently needs to expand its construction floor space. A crucial challenge lies in the constraints of the existing urban structure, which cannot be overlooked due to the considerable economic and social costs related to demolishing old buildings and relocating individuals and companies. This paper will next focus on Shanghai's future land development and provide insights for designing more efficient land policies. This exercise will be achieved using the previously established theoretical framework and parameters that have been calibrated or estimated.

According to Shanghai's 2017-2035 Master Plan, an additional 270 million square meters of floor space will be constructed, supplementing the existing floor space stock of 1,050 million square meters between 2015 and 2035, a rough increase of 30%. Consequently, a significant amount of new land development quota will be granted, and allocating this new quota across Shanghai becomes a critical decision, along with zoning restrictions and building height limitations. In our next analysis, we

[35] Notice that in equilibrium, the total floor space supply of the whole city is 7.8% lower than the initial level.

concentrate on examining various future development plans related to land quota allocation across space. This analysis will be conducted under the condition that the existing floor space layout (floor space supply and building heights on the already developed land) remains unchanged.

As a fresh benchmark, we execute *Counterfactual NewC0*, where the city government merely allocates the new floor space in a way to imitate both the spatial and sectoral distributions of the original floor space.[36] Specifically, each street tract is allocated the same proportion of the total new floor space as it had in the allocation of the total initial floor space. In addition, the building height is maintained at the original level. The new land development quota granted to each street tract is thus determined by dividing the new floor space by the initial building height. Furthermore, within each street tract, the ratio of residential floor space to business floor space remains the same as initially dictated by the zoning restrictions. As expected, in the new equilibrium, the spatial distributions of both residential and workplace employment remain quite similar to the initial ones, as seen in Figure 10, Panels A and D. However, due to a 30% increase in the total floor space supply, there is a welfare gain of 8.7% compared to the initial level. Next, we will compare various alternative development plans with *Counterfactual NewC0*.

[Figure 10 about here]

Firstly, in *Counterfactual NewC1*, we allow the market to play its role in allocating the new floor space. Specifically, developers have the freedom to choose any street tract around the city on which to build, and can set the building heights based on market signals. To ensure the newly added floor space supply aligns with the 270 million square meters outlined in the city's Master Plan, the government allocates new land quotas to each street tract in proportion to its total available land.[37] We also permit free arbitrage between land use types. Essentially, in this counterfactual, market forces dictate the distribution of new floor space across different locations and usage types. The welfare gain relative to the initial benchmark level is 14.9%. Compared with the welfare gain of 8.7% in *Counterfactual NewC0*, the additional gain from allowing market forces to determine the spatial allocation of new floor space is 6.2%. Figure 10, Panels B and E, show noticeable changes in the spatial distribution of both residential employment and workplace employment across localities in *Counterfactual NewC1*, compared to *Counterfactual NewC0*. These new spatial distributions align more closely with local fundamental amenities.

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[36] We exclude Chongming Island from allocating new floor space in all of the counterfactual analyses in Section 8 for the same reasons discussed in Section 7.

[37] Without the constraint of the 270 million square meters cap, developers could build on all the available land in any street tract they choose.

Secondly, we investigate hybrid plans that blend market forces with governmental interventions regarding the land development quota assignment. In such alternative plans, the city government grants development quotas only to a selective region of the city. The Shanghai government has two candidate policies concerning the city's future spatial development. One plan focuses on the nine designated subcenters of the city, while the other aims to develop the edge towns intensively. Informed by these plans, we conduct two additional counterfactual analyses.

In *Counterfactual NewC2*, the city allows developers to only conduct new land development in the nine subcenters of Shanghai. The government allocates a new land quota to each subcenter street tract in proportion to its total available land, ensuring the newly added floor space supply aligns with the 270 million square meters outlined in the city's Master Plan. Within these subcenters, the construction of floor space still follows the market signals as in *Counterfactual NewC1*. We also allow free arbitrage between land use types. Notably, these subcenters exhibit high local production fundamentals (as indicated in Figure 6, Panel A) and decent residential fundamentals (Figure 6, Panel B). This prioritization of development in the subcenters significantly stimulates agglomeration economies, leading to large productivity gains, evident from the substantial increase in the average wage compared to the purely market-oriented development plan in *Counterfactual NewC1* (see Table 8, column (2)). Moreover, there is a significant improvement in the average residential amenities (Table 8, column (6)). Commuting length and time decrease by 16.2% and 12.9%, respectively, compared to *Counterfactual NewC1* (Columns (4) and (5) in Table 8). The residential housing price slightly increases compared to *Counterfactual NewC1* (column (3) of Table 8). Overall, the welfare gain achieved through *Counterfactual NewC2* is 21.1% relative to the initial benchmark level, surpassing the gains from *Counterfactual NewC1* and *Counterfactual NewC0* by 6.2% and 12.4%, respectively.

Our findings suggest that prioritized development in the subcenter regions is a sensible approach for Shanghai's future growth. Given the historical constraint of the existing floor space layout and spatial misallocation (as discussed in Section 7), the initially less-densely developed subcenters may not appear as attractive to people and jobs following market signals as other locations that are initially densely populated, even though the subcenters have better fundamentals than those locations. As a result, the potential of agglomeration economies might not be fully realized. Moreover, even though historically high-density locations are becoming increasingly congested, market forces may not fully account for the negative externality. Therefore, under historical constraints, the city government might consider adopting a hybrid policy for new development that prioritizes the development of subcenters in land quota allocation while allowing market forces to play their roles within the subcenters. This future development plan may help resolve the coordination failure caused by externalities and, in turn, enhance welfare compared to a market-oriented development.

In Figure 10, Panels C and F, we present the spatial distribution of residential and workplace employment densities in *Counterfactual NewC2*. By directing new floor space to the subcenters, both the population and jobs flow to these subcenters, stimulating agglomeration economies and shortening commuting distances. Meanwhile, there is still a concentration of jobs in the traditional city core, but the density is lower than *Counterfactuals NewC0 and NewC1*, which may alleviate congestion. Multiple centers are formed in Shanghai, attracting people and jobs from other parts of the city. It is worth noting that the subcenters are generally located 10-20 km away from the city core, allowing them to benefit from spillover effects from each other.

Finally, we also explore allocating all the land development quotas to the five edge towns, referred to as *Counterfactual NewC3*.[38] Despite a significant drop in housing prices, the welfare gain achieved is 12.2% relative to the initial level. This is lower than the case of *Counterfactual NewC1* and substantially lower than the case of *Counterfactual NewC2*, although it is higher than *Counterfactual NewC0*. The limited welfare improvement can be mainly attributed to the low productivity in the edge towns. There are two reasons for this low productivity. One is the poor production fundamentals in these edge towns, such as inadequate transportation infrastructure. The other reason is that the edge towns are located far from the city core area (50-60km), which hinders the positive spillovers from the core.

9. Discussions: An Alternative Model without Endogenous Traffic Congestion

A key contribution of our baseline model is that it incorporates the congestion effect endogenous to densities. Specifically, we let the bilateral commuting time depend on the residential employment density at the origin, the workplace employment density at the destination, and the cross-traffic flows along the route, in addition to bilateral distances. In this section, we consider an alternative model that does not incorporate the influence of densities on commuting time, allowing the bilateral commuting time to depend solely on exogenous factors such as distances. We shall present counterfactual results based on this alternative model and discuss how these results differ from those of the baseline model.

9.1 Fitness of the alternative model for the actual data

We first check the explanatory power of this alternative model for the actual data. According to Eq.

[38] Similar to *Counterfactual NewC2*, in *Counterfactual NewC3,* the city allows developers to only conduct new land development within the five edge towns by designating new land quotas to them at a level proportional to each edge town tract's available land and ensuring the newly added floor space supply matches the 270 million square meters outlined in the city's Master Plan.

(22), we eliminate the influence of densities at both the origin and the destination and the influence of the cross-traffic along the route on the real bilateral commuting time, obtaining a residual bilateral commuting time matrix. We scale up this residual matrix to let its mean equal the mean of the real bilateral commuting time matrix. The resulting bilateral commuting time thus only depends on the bilateral distance and other exogenous factors. Meanwhile, the average time is still the same as the actual data. Based on it, we run the counterfactual of the benchmark case corresponding to the current land use regulations using the alternative model.

In Panel A, Figure 11, we plot the equilibrium bilateral commuting flows predicted by the alternative model against the actual flows in the data, as we did in the over-identification checks in Section 6.2. The correlation coefficient is 0.8284, notably smaller than the correlation coefficient between the flows predicted by the baseline model and the actual ones (0.9131). This finding indicates that the alternative model's explanatory power for the actual data becomes weaker. In Panel B, Figure 11, we present the cumulative probability curves of bilateral commuting flows plotted against the commuting distances for the observed data, baseline model predictions, and alternative model predictions. Once more, it is evident that the model's explanatory power weakens without accounting for endogenous congestion effects. Furthermore, for this alternative model, we observe that people's working places and living places are more likely to be separated, and the bilateral commuting distance becomes more dispersed. This is because, without congestion concerns, firms and residents are more likely to gravitate towards localities with attractive production and residential amenities.

[Figure 11 about here]

9.2 Counterfactual results using the alternative model

We then re-run all the counterfactual analyses from Sections 7 and 8 based on this alternative model. We assume the bilateral commuting time is fixed constant at the current data level regardless of the re-distribution of jobs and people caused by counterfactual land policies changes. The equilibrium outcomes are reported in Table 9. Additionally, the corresponding spatial distributions of residence and workplace employment densities are presented in Figures A6 and A7 in Appendix A, respectively.

[Table 9 about here]

First, let us examine *Counterfactual C2*, where we keep each street tract's land development area at the initial level while relaxing zoning restrictions on land use types and building height constraints. Figure A6 Panel C shows that residential employment has decentralized further from the city core than predicted by the baseline model. Moreover, residential employment is highly concentrated in several street tracts far from the city core, with a density much higher than that predicted by the baseline model. This pattern emerges because agglomeration can be drastic without the congestion effect as a counterbalance. Column (1) of Table 9 shows that the welfare gains from introducing market forces are substantially higher than predicted by the baseline model. This could be explained by the considerable increases in average wage and living amenities driven by high agglomeration economies of production and residence, compared to the predictions of the baseline model (see Table 9, columns (2) and (6)). The drop in housing prices is more pronounced than in the baseline model, likely due to the decentralization of the residential population to street tracts far from the city core. The average commuting distance also increases due to the decentralization of residential employment from the city core.

Next, we look at *Counterfactuals NewC1*, *NewC2*, and *NewC3*, where we assign new land development quotas to certain areas of the city while introducing market forces to allocate the new floor space across different street tracts within those designated development areas. We also allow free arbitrage between land use types. We notice that the welfare gains, in general, are substantially larger than predicted by the baseline model, likely due to the highly agglomerated and more decentralized residential employment, leading to substantial increases in living amenities and lower housing prices. Similar to the baseline model prediction, prioritized development in the subcenters (i.e., *Counterfactual NewC2*) yields the most substantial welfare gains. However, the difference in welfare gains between *Counterfactual NewC2* and the market-oriented plan *Counterfactual NewC1* is much smaller than in the baseline model. Since no negative externalities arise from the congestion effect in this alternative model, the coordination problem of the purely market-oriented plan *Counterfactual NewC1*, as discussed in Section 8, is less severe than in the baseline model.

Overall, while this alternative model without traffic congestion can generate insights similar to those from the baseline model, the predicted pattern of spatial redistribution of people is more dramatic and less realistic in the counterfactual analyses compared to the predictions of the baseline model. This is due to the model shutting down the congestion effect of density, which is more likely to lead to drastic agglomeration of people or jobs.

10. Conclusion

The internal urban structure has a profound welfare impact, especially for densely populated metropolises worldwide. Cities thrive on agglomeration economies, but large metropolises are plagued by congestion and housing costs due to high densities. Optimizing the inner city structure to balance these two opposing forces and improve welfare is a complex and intriguing task. This paper tackles this challenge from the perspective of land use regulations, which involve determining the quantity, location, and types of land development. These decisions have a lasting impact on the spatial organization of people and firms within the city.

This paper first develops a workhorse model for an extensive analysis of the GE effects of land use regulations. Our innovation lies in expanding the standard quantitative model of internal urban structure to include both positive and negative externalities of densities. Our analysis is based on this model and a newly constructed, spatially disaggregated dataset for Shanghai, China's largest metropolis.

We emphasize the importance of leveraging market forces to guide spatial development when designing land use policies. Through counterfactual analyses, we demonstrate the spatial misallocation and potential welfare losses caused by the current restrictive zoning and building height constraints. Allowing free arbitrage between residential and business land can yield a welfare gain of 6.7% relative to the initial level. Moreover, lifting building height constraints to allow floor space supply to respond to local market signals can generate an additional welfare gain of 2.4%. These welfare gains are primarily the result of enhanced agglomeration economies and reduced housing costs.

Furthermore, this paper also provides important insights that could guide future spatial development in metropolises that urgently need to expand their construction space. The findings of this paper suggest that while designing land use regulations that better align with market demand would generally enhance efficiency, introducing government interventions might be necessary to address the coordination failure due to a city's historical layout that presents spatial misallocation. Specifically, regarding the construction of an additional 270 million sqm of new floor space as outlined in Shanghai's Master plan 2017-2035, we demonstrate that a development strategy that prioritizes the creation of subcenters represents a sensible approach for Shanghai's future growth. This approach could lead to a welfare gain of 21.1% compared to the initial level, surpassing an alternative development plan that allows developers to build throughout the city following market signals by 6.2%.

This paper opens up avenues for future research in various directions. For example, there is merit in delving deeper into the interactions between land use regulations, transportation infrastructure development (e.g., subway expansions), and the evolution of commuting habits (e.g., the rise of bike and car-sharing schemes and the adoption of remote work) in shaping the spatial layout of economic activities. It would also be interesting to consider commercial activities and consumption travels in the model. Moreover, it would be beneficial to integrate demographic heterogeneity into the analysis (e.g., gender, income, and education levels), as different demographic groups may have different values of locational amenities and react differently to changes in travel times. Additionally, given the ongoing structural transformations in many urban areas globally, it would be valuable to explore how our model's predictions are impacted by changing the values of the critical parameters, such as those defining agglomeration economies, commuting costs, and construction costs.

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