Why did Highways Cause Suburbanization? The Role of Highway Congestion*

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Abstract

Congestion is a large problem in metropolitan areas. This paper provides a theoretical and empirical framework that can analyze whether congestion induced by highway construction affects residential and workplace choice in metropolitan areas. First, we develop a quantitative urban model with congestion, and this model illustrates that how congestion affect the worker location choices of residence and workplace. This model indicates that congestion induced by highway construction causes population and employment suburbanization. To examine the validity of the model, we use partial identification with data on central cities in US from 1950 to 1990. The empirical results shows that the model with congestion is evidenced by the data on all cities. On the other hand, the model without congestion is not valid the data on congested central city.

JEL classification R11, R12, R14, R40

Keywords Suburbanization, Traffic congestion, Highways, Commuting cost

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1 Introduction

Congestion is a large problem in metropolitan areas. Couture et al. (2018) investigate the determinants of driving speed in US metropolitan areas and estimate that the dead weight loss from congestion is around \$30 billion per year. Meanwhile, Sweet (2014) suggests that traffic congestion troubles employment growth and productivity growth per worker. Moreover, Duranton and Turner (2011) and Hsu and Zhang (2014) find that vehicle-kilometers traveled on interstate highways in metropolitan areas increase one-for-one with the supply of interstate highways in US and Japanese cities. Downs (1962, 1992) terms this phenomenon the *fundamental law of highway congestion*. The deeper point here is that fundamental law suggests that investments in transportation infrastructure do not, on average, decrease congestion in large metropolitan areas.[1] In addition, since the construction of highways has fostered population growth in metropolitan areas (Duranton and Turner, 2012), highway construction is one of the source of congestion in metropolitan area.[2]

This paper provides theoretical and empirical evidence of the effect of congestion induced by highway construction on the distribution of population and employment in metropolitan areas. We first develop a spatial equilibrium model that incorporates heterogeneity in commuting technology, that is, in surface roads and highways, and that is focus on highway congestion. In short, we incorporate congestion in commuting into canonical urban model (e.g., Lucas and Rossi-Hansberg, 2002; Ahlfeldt et al., 2015). Our theoretical model allows for an arbitrary number of heterogeneous locations that differ in terms of productivity, amenities, density of development, and commuting. Productivity depends on production externalities, such as agglomeration externality, which are determined by the density of workers. Amenities also depend on residential externalities, which are determined by the density of residents. The spatial distribution of economic activity is determined by a tension between agglomeration and dispersion force. Forces for the agglomeration of economic activity take the forms of production and resident externalities, while forces for dispersion take the forms of land supply, commuting costs, and congestion.

According to our theoretical model, congestion induced by the construction of highways helps explain the mechanism of population and employment suburbanization. Highway congestion is

[1] According to the Texas Transport Institute's congestion index, congestion costs amounted to \$901 in 1985 and \$1,385 in 2010, and delay per peak auto commuter was 28 person-hours in 1985 and 49 person-hours in 2010 in 101 US urban areas.

[2] Some residents protest highway construction through what are called *freeway revolts*, with protests having been staged in many US cities; see Brinkman and Lin (2019).

causing commuting costs to increase in step with highway construction, especially in the city centers of metropolitan areas. Since congestion work as a dispersion force, workers tend to choose to move to and work in suburban areas to avoid congestion, even though wages are often higher in central city. These trends toward suburbanization are in line with the results of recent empirical evidence.

Recent empirical studies suggest that highway construction led to the decentralization both of population and employment in the central cities of metropolitan area. For instance, Baum-Snow (2007a) shows that the population of a central city decreases by 18% when a new highway passes through the central city in a US metropolitan area. In addition, Baum-Snow et al. (2017) and Garcia-López et al. (2015) find that the introduction of a new highway reduced the central city population in metropolitan areas in Spain and China.[3] In addition, some empirical research addresses the effect of highway or railroad construction on employment suburbanization. For instance, Baum-Snow (2019) indicates that the central cities of the largest 100 metropolitan areas in US had a 61% employment share in 1960 that fell to 34% in 2000, and a new radial highway displaced approximately 5% of employment to suburban areas.[4] In addition, Baum-Snow (2010) notes that a reduction in transportation costs changes the commuting pattern in large metropolitan areas. Specifically, new highway construction decreases the number of commuters who live and work in a central city and increases the number of commuters who live in the suburbs and work outside a central city. In other words, new highway construction decentralizes residents and employment.[5] Along these lines, the implications of our theoretical model, highway construction decrease central city population and employment, are in line with recent empirical research on population and employment decentralization.[6]

This paper provides empirical evidence to support its theoretical model by using partial

[3]Resident decentralization in central cities in the metropolitan areas of Spain and China is slightly different from that in US in terms of absolute and relative decline. Central city populations in US metropolitan areas decreased, while the populations in Spanish and Chinese central cities did not decrease during the study period. Compared with the population change in metropolitan areas, the population change in central cities was lower. Baum-Snow et al. (2017) and Garcia-López et al. (2015) define this change as suburbanization. For instance, in Spanish metropolitan areas, the change in log central city populations from 1960 to 2011 is 0.79, while it is 0.86 in metropolitan areas. Both are increasing, but the growth in central city populations is smaller than that in metropolitan areas. We call this *relative* suburbanization, and this paper defines suburbanization as *relative* suburbanization.

[4]The numbers of employed persons in central cities and metropolitan areas in 1960 were 23.3 and 36.8 million, respectively, while the numbers of employed persons in these areas in 2000 were 26.2 and 71.1 million, respectively.

[5]Garcia-López et al. (2017b) focus on the causal effect of constructing commuting transportation on sub-center formation in Paris, France. The authors found that transportation construction increases the number of subcenters. Meanwhile, Garcia-López and Muñiz (2010) find that employment was decentralized and polycentricity reinforced in Barcelona from 1986 to 2001.

[6]Some empirical results analyzed by historical data show employment centralization. For instance, Heblich et al. (2018) show that commuting railroads constructed between 1850 and 1920 in London promote population suburbanization and employment centralization.

identification.[7] Ultimately, this paper argues that congestion is necessary to consider when interpreting changes in the distribution of population and employment in metropolitan areas after new highway construction. The data on cities in metropolitan areas in US between 1950 and 1990 is used for analysis. This study faces two challenges with empirical analysis. First, regardless of congestion, highway construction causes population suburbanization—that is, even though existing literature shows the causal effect of highway construction on population and employment decentralization, they do not mention the mechanism of suburbanization. To examine the validity of a theoretical model that includes congestion, we focus on how the implications of the model with congestion differ from those of the model without congestion. The difference turns out to be the relationship between the number of highway rays in central cities and population reduction in central cities. More specifically, the theoretical model with congestion indicates that the relationship is monotone decreasing, while the theoretical model without congestion indicates that the relationship is convex and monotone decreasing. This difference comes from the dispersion force in the model, and enables us to examine the validity of the theoretical model with congestion by partial identification.

The second challenge is that empirical literature evaluating the effect of improvement in transportation infrastructure has endogenous problem that transport infrastructure is not assigned randomly. Highways typically serve populated cities or cities that are expected to show population growth. A standard approach to carefully establishing the causal relationship involves using an instrumental variable based on historical transportation networks (Duranton and Turner, 2012; Garcia-López, 2012; Garcia-López et al. 2015), straight-line connections between large metropolitan area (Banerjee et al. 2012; Hornun, 2015), or planned route networks (Baum-Snow, 2007a). This paper employs the planned route networks, that is, we use a 1947 planned highway route as an instrument variable.

The results of empirical analysis imply that the theoretical prediction with highway congestion is evidenced by all cities in US metropolitan areas; however, the theoretical prediction without highway congestion related to canonical urban models is not evidenced by the data on populated central cities. According to Baum-Snow (2007a), one additional highway decreases a central city's population by approximately 10%. However, the results with data on populated central cities point out that the causal effect of highway construction on central city population is at most -9% under the assumptions of convex and monotone decreasing (related to the model without congestion). This indicates that the model without congestion (related to canonical

[7] Partial identification was originally suggested by Manski (1989).

urban models) are not evidenced by data on populated central cities. On the other hand, based on our theoretical model's prediction, the causal effect of constructing one additional highway is at most -21%, that is, our theoretical model (including congestion) is evidenced by the data on populated cities.

Understanding the effect of congestion induced by improvement in transportation infrastructure is important for several reasons. First, even though congestion is one of the biggest problems in metropolitan area, the effect of congestion on workers' residential and workplace location choice remains largely unexplored to the best of our knowledge. For example, Sweet (2014) shows that traffic congestion drags employment growth and productivity growth per worker, and Hou (2017) shows that firms belongs to the sector which requires high-order office activities are tend to avoid congestion; however, we do not know the mechanism of these results. Second, investment in transportation infrastructure affects land use patterns such as household and firm location choice; as a consequence, transportation networks affect individual welfare, firm productivity, and GDP in metropolitan areas—for instance, highway construction causes population suburbanization (Baum-Snow 2007; Garcia-López et al., 2015) and fosters urban growth (Duranton and Turner, 2012). In other words, investment in transportation infrastructure impacts public policy interventions such as those related to urban development and taxation. Moreover, the construction of transportation infrastructure requires a great deal of investment. In the US, the construction of the interstate highway system began in 1956 and took 35 years and $144 billion to complete (Minnesota Department of Transportation, 2006).[8]

Our paper builds on the large collection of literature on urban economics. Many of these papers assume a monocentric city model, in which firms are located in a central business district (CBD) and workers choose their place of residence by considering the trade-off between commuting cost and land price.[9] Fujita and Ogawa (1982) were the first to develop a theoretical model of urban land use without CBD, in other words, this model can analyze workers and firms location choice in metropolitan area. This model indicates that, in equilibrium, economic activity can be non-monocentric when commuting cost is high. Lucas and Rossi-Hansberg (2002) extend Fujita and Ogawa's model to that of two-dimensional city. This model assumes that space is continuous and the metropolitan area symmetric. Meanwhile, Ahlfeldt et al. (2015) developed a quantitative theoretical model of urban land use that is tractable and that assumes asymmetric locations. This model enables us to solve for the unique wage equilibrium informing

[8]The initial estimated cost for this interstate highway system was $25 billion. This was the largest public project in US history at the time.

[9]See Alonso (1964), Mills (1967), and Muth (1968) for more information on the monocentric city model.

residential and workplace decisions in metropolitan areas. In equilibrium, firms balance the benefits of agglomeration externality against the disutility of worker commutes. Here, it is helpful to note that canonical urban models influence government policies such as zoning, tax, and transportation investment. This paper contributes to such existing literature by arguing that congestion emerges as a stronger dispersion force in modern urban areas with large populations than canonical urban models assume. We test the implication of our theoretical model using data on US metropolitan areas.

This paper is the first to develop a framework that can analyze whether congestion affects residential and workplace choice in metropolitan areas, assuming that congestion occurs endogenously. To be sure, some studies already exist on equilibrium outcomes and urban spatial structure. Anas and Kim (1996) were the first to develop a general equilibrium model of urban land use with land markets, mobile agents, and externalities. In addition, Baum-Snow (2007b) shows the effect of highway construction with congestion on population in central cities; notably, this model is based on the monocentric city model, that is, it focuses only on workers. Some existing studies on congestion, such as those by Anas and Kim (1996), Brinkman (2016), and Brinkman and Lin (2019) have insightful implications. For instance, Brinkman (2016) estimates the structural parameters of the spatial equilibrium model of urban structure with congestion on commuting and finds that congestion pricing leads to negative economic outcomes, such as employment decentralization and the loss of agglomeration externalities. Our paper indirectly supports these findings by suggesting a framework for examining whether congestion related to commuting impacts workers' residential and workplace decisions.

Our paper is also related to the broader literature on the effect of investment in transportation infrastructure on economic activity. At the intra-metropolitan level, the effect of highway or railroad construction on population and employment decentralization, as in Baum-Snow (2007, 2019) for US; Baum-Snow et al. (2017) for China; Bollinger and Ihlanfeldt (1997) for Atlanta; Garcia-López (2012) for Barcelona; Garcia-López et al. (2015) for Spain; Garcia-López et al. (2017a; 2017b) and Mayer and Trevien (2017) for Paris; and Gonzalez-Nabarro and Tuner (2018) for metropolitan areas around the world—as well as Gibbons et al. (2019) on firm productivity; Holl (2016), Billings (2011), and Gibbons and Machin (2005) on real estate prices; and Baum-Snow (2010) on commuting patterns.[10] In addition, Ahlfeldt et al. (2015) investigate the changes in transportation networks induced by the Berlin Wall on workers' residential and workplace choices.[11] This paper distinguishes itself from these empirical studies by providing

[10]See Redding and Turner (2015) for a review of the effect of infrastructure on urban and regional outcomes.

[11]At the metropolitan level, reduced transportation costs increase regional outputs such as population, employ-

a theoretical framework for the micro-foundation of these results by incorporating congestion related to commuting.

The remainder of this paper is organized as follows. In Section 2, we develop a theoretical model and report the results of the numerical calculation. In Section 3, we introduce the data in detail and outline the partial identification estimation methodology. Section 4 presents the results of the point estimation and partial identification to investigate the validity of the model. The final section concludes the paper.

2 Theoretical Model

We develop a theoretical model based on the canonical urban model suggested by Ahlfeldt et al. (2015) with the addition of congestion induced by highway construction. This model illustrates the effect of highway construction on worker choice of residence and workplace location.

Our model considers a metropolitan area embedded within a wider economy. A metropolitan area consists of a set of locations that include the central city and suburban cities, $M = \{c, s_1, s_2, \cdots, s_f\}$.[12] The central city is located at the center of the metropolitan area, and suburban cities are located around the central city. We assume that this metropolitan area is an *open city* setting; in other words, the number of workers is determined endogenously, $\bar{L}$.[13] Each worker chooses a residence i and a workplace j from the set of cities, $(i, j \in M)$, and workers can move within a metropolitan area, which implies that the expected utility is the same within the metropolitan area and the rest of the economy, $\bar{U}$. In addition, each worker is endowed with one unit of labor that is supplied inelastically. Firms produce a final consumption of goods that trade at no cost within the metropolitan area. In addition, a landlord owns the floor space.

ment, GDP, income, and trade; see Chandra and Thompson (2000) and Duranton and Turner (2012) for the US; Alder (2019) and Datta (2012) for India; Audretsch et al. (2017) for Portugual; Baum-Snow et al. (2018), Banerjee et al. (2012), Faber (2014), Lin (2017), and Yu et al. (2018) for China; Fretz et al. (2017) for Switzerland; and Ahlfeldt and Feddersen (2018), Heuermann and Schmieder (2019), Möller and Zierer (2018), Redding and Sturm (2008) for Germany. In addition, Berger and Enflo (2017), Donaldson (2018), Donaldson and Hornbeck (2016), Heblich et al. (2018), Hodgson (2018), and Hornung (2015) focus on the construction of transportation infrastructure in the 19th century.

[12] c and s_{-} indicate the central city and suburban cities, respectively.

[13] According to Duranton and Turner (2012), highway construction led to population increases in US metropolitan areas; hence, we use an open city setting.

2.1 Theoretical Model Settings

2.1.1 Workers

The preference of a worker o residing in i and working in j is composed of final goods consumption c_{ij}, consumption of the residential floor space h_{ij}, and an idiosyncratic amenity shock b_{ijo}. We assume that the utility takes the Cobb-Douglas form:[14]

$$U_{ijo} = b11\frac{b_{ijo}}{k_{ij}}\left(\frac{c_{ij}}{\alpha}\right)^{\alpha}\left(\frac{h_{ij}}{1-\alpha}\right)^{1-\alpha}, \tag{1}$$

where $0 < \alpha < 1$ and k_{ij} is an iceberg-type commuting cost, $k_{ij} \in [1, \infty)$.[15] In addition, this model has heterogeneous utility. We draw the idiosyncratic amenity shock, b_{ijo}, from the independent Fréchet distribution for each residence and workplace pair:

$$G_{ij}(b) = e^{-B_i b^{-\epsilon}}. \tag{2}$$

The scale parameter, $B_i > 0$, captures the average amenities from living in i, such as a beautiful view. The shape parameter, $\epsilon > 1$, controls the dispersion of amenities.

Each worker chooses a residential and workplace city to maximize utility with the given residential amenities, final goods, and floor price, as well as the location choice of other workers and firms. As noted above, each worker has one unit of labor that is supplied inelastically. With first-order conditions for maximizing utility, we obtain the demand function for the final goods and residential land for living in i and working in j:

$$c_{ij} = \alpha\frac{w_j}{P_i}, \tag{3}$$

$$h_{ij} = (1-\alpha)\frac{w_j}{Q_i}, \tag{4}$$

where w_j is the wage received in city j, and Q_i is the floor price in city i. The aggregate consumption in i of the final goods C_i and land for workers H_i^W are

$$C_i = \alpha\frac{\bar{w}_i R_i}{P_i}, \tag{5}$$

$$H_i^W = (1-\alpha)\frac{\bar{w}_i R_i}{Q_i}, \tag{6}$$

[14] The Cobb-Douglas functional form of constant housing expenditure is supported by US data; see Davis and Ortalo-Magné (2011).

[15] This model assumes commuting cost in terms of utility. This model captures the effect of highway construction in the opportunity cost of commuting. According to Ahlfeldt et al. (2015), this assumption is isomorphic in terms of a reduction in the effective units of labor.

where $\bar{w}_i$ is the expected wage of the worker residing in i, and R_i is the number of residents. Substituting the consumption of final goods, (3), and residential land use, (4), into the utility function, (1), we obtain the indirect utility function:

$$U = \frac{b_{ijo} w_j}{P_i^{\alpha} Q_i^{1-\alpha} k_{ij}}. \tag{7}$$

2.1.2 Residence and workplace choices

This section shows the probability that a worker chooses a residence and workplace. All necessary model derivations are shown in Appendix A.1. We assume that the idiosyncratic amenity shock b_{ijo} follows a Fréchet distribution. Hence, the distribution of utility for worker o residing in i and working in j also follows a Fréchet distribution:

$$G_{ij}(u) = e^{-\psi_{ij} U^{-\epsilon}}, \tag{8}$$

where $\psi_{ij} = B_i (P_j^{\alpha} Q_i^{1-\alpha} k_{ij})^{-\epsilon} w_j^{\epsilon}$. According to this distribution, the probability that a worker chooses city i as the residence and city j as the workplace, λ_{ij}, is

$$\begin{aligned} \lambda_{ij} =& \frac{L_{ij}}{\bar{L}} \\ =& \frac{B_i \left(P_i^{\alpha} Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^{\epsilon}}{\sum_r^M \sum_t^M B_r \left(P_r^{\alpha} Q_r^{1-\alpha} k_{rt}\right)^{-\epsilon} w_t^{\epsilon}}, \end{aligned} \tag{9}$$

where L_{ij} is the number of commuters from i to j, and $\bar{L}$ denotes the total employment in the metropolitan area. This probability shows that workers select their residence and workplace based on the characteristics of residence i and workplace j, but also the characteristics of the other cities. We obtain the probability that a worker chooses city i as the residence by summing these probabilities across the workplace for the given residence:

$$\begin{aligned} \lambda_i^R =& \sum_j^M \lambda_{ij} \\ =& \frac{\sum_j^M B_i \left(P_i^{\alpha} Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^{\epsilon}}{\sum_r^M \sum_t^M B_r \left(P_r^{\alpha} Q_r^{1-\alpha} k_{ij}\right)^{-\epsilon} w_t^{\epsilon}}. \end{aligned} \tag{10}$$

On the other hand, summing these probabilities across residences for a given workplace, we obtain the probability that a worker chooses city j as the workplace:

$$
\begin{aligned}
\lambda_j^L &= \sum_i^M \lambda_{ij} \\
&= \frac{\sum_i^M B_i \left(P_i^\alpha Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^\epsilon}{\sum_r^M \sum_t^M B_r \left(P_r^\alpha Q_r^{1-\alpha} k_{rt}\right)^{-\epsilon} w_t^\epsilon}.
\end{aligned} \tag{11}
$$

The conditional probability that a worker residing in i chooses city j as the workplace, $\lambda_{ij|i}^R$, is

$$
\begin{aligned}
\lambda_{ij|i}^R &= \frac{B_i \left(P_i^\alpha Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^\epsilon}{\sum_t^M B_i \left(P_i^\alpha Q_i^{1-\alpha} k_{it}\right)^{-\epsilon} w_t^\epsilon} \\
&= \frac{(w_j/k_{ij})^\epsilon}{\sum_t^M (w_t/k_{it})^\epsilon}.
\end{aligned} \tag{12}
$$

This conditional probability implies that workers residing in i decide their workplace based on only wages and commuting cost. Using this conditional probability, the commuter market clearing condition implies

$$
\begin{aligned}
L_j &= \sum_i^M \lambda_{ij|i}^R R_i \\
&= \sum_i^M \frac{(w_j/k_{ij})^\epsilon}{\sum_t^M (w_t/k_{it})^\epsilon} R_i,
\end{aligned} \tag{13}
$$

which means that the number of workers who work in j equals the sum of the workers who choose city j as the workplace. In addition, the expected wages of workers residing in i, $\bar{w}_i$, is equal to the wages in all possible workplaces weighted by the probabilities of commuting to those workplaces conditional on living in city i:

$$
\begin{aligned}
\bar{w}_i &= \mathbb{E}[w|i] \\
&= \sum_j^M \lambda_{ij|i}^R w_j \\
&= \sum_j^M \frac{(w_j/k_{ij})^\epsilon}{\sum_t^M (w_t/k_{it})^\epsilon} w_j.
\end{aligned} \tag{14}
$$

The expected wage is high in cities whose commuting costs are lower than those in high-wage employment cities. Finally, the assumption of mobile workers implies that the expected utility for all pairs of residence and workplaces is equal to the reservation level of utility in the wider economy, $\bar{U}$:

$$\begin{aligned}\bar{U} :=& \mathbb{E}[u] \\ =& \eta \left[\sum_{r}^{M} \sum_{t}^{M} B_r (P_r^{\alpha} Q_r^{1-\alpha} k_{rt})^{-\epsilon} w_t^{\epsilon} \right]^{1/\epsilon}, \end{aligned} \tag{15}$$

where $\eta = \Gamma[(\epsilon-1)/\epsilon]$ and $\Gamma[\cdot]$ is the gamma function.

2.1.3 Producers

We refer to the canonical urban land use model, which assumes that a single final good is produced under conditions of perfect competition and constant returns to scale. Production requires labor and floor space, and the production technology is in Cobb-Douglas form. For simplicity, the final good is costlessly traded; therefore, the price of the final good is the same, $(P_j = P)$. The output of the final good, y_j, in city j is

$$y_j = A_j L_j^{\beta} \left(H_j^F \right)^{1-\beta}, \tag{16}$$

where A_j is final good productivity, L_j is workplace employment, and H_j^F is floor space for firm.

Firms choose their inputs of workers and floor space to maximize their profit. With the first-order conditions for profit maximization, we obtain the demand for floor space:

$$H_j^F = \left[\frac{(1-\beta) A_j}{Q_j} \right]^{1/\beta} L_j. \tag{17}$$

Floor space for firms increases with productivity A_j and employment L_j, and decreases for floor price Q_j. In addition, from zero profits and the first-order conditions for profit maximization, the equilibrium wage in each city with a positive floor price must satisfy

$$w_j = \beta A_j^{\beta} \left(\frac{1-\beta}{Q_j} \right)^{(1-\beta)/\beta}. \tag{18}$$

Intuitively, the equilibrium wage increases with productivity A_j, and the lower floor price q_j increases wages.

2.1.4 Land market

We assume that the landlord owns the floor space for workers and firms, and the price of floor space for each is the same. The land market clearing condition implies that the demand for floor space for residents (6) and firms (17) equals the supply of floor space:

$$\begin{aligned} H_i =& H_i^W + H_i^F \\ =& (1-\alpha)\frac{\bar{w}_i}{Q_i}R_i + \left(\frac{(1-\beta)A_i}{Q_i}\right)^{1/\beta} L_i. \end{aligned} \tag{19}$$

In addition, H_i is determined by the geographical land area K_i and the density of development d_i. The density of development is measured by the ratio of floor space to land area. We refer to Saiz (2010) and represent the supply of floor space as

$$\begin{aligned} H_i =& \quad d_i K_i, \\ d_i =& \quad d Q_i^{\mu}, \end{aligned} \tag{20}$$

where d is a constant and μ is the elasticity of the floor space. $\mu = 0$ implies that the supply of floor space is perfectly inelastic.

2.2 Equilibrium

Given the parameters in our model $\{\alpha, \beta, \mu, \epsilon, d\}$, reservation utility level in the wider economy $\bar{U}$, and exogenous location characteristics vector $\{\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{k}\}$, the general equilibrium of this model is referenced by the vector $\{\boldsymbol{L}, \boldsymbol{R}, \boldsymbol{Q}, \boldsymbol{w}, \bar{\boldsymbol{w}}, \bar{L}\}$.[16] Given this equilibrium vector and scalar, the other endogenous variables can be determined. The following sets of equations determine the equilibrium vector: workplace choice probabilities (11), residential choice probabilities (12), expected wage in residential city i (14), zero-profit conditions (18), land market clearing conditions (19), and population mobility (15). We provide conditions for the existence and uniqueness of the general equilibrium of this model in Appendix A.2.

Since we cannot solve this model analytically, we use numerical calculations to analyze the effect of highway construction on worker residence and workplace choices. In addition, this model assumes that location characteristics (e.g., productivity A_j) are exogenous; hence, we add the agglomeration externalities and congestion into this model in the next section.

[16]Bold math font indicates vectors or matrices.

2.3 Numerical calculations

2.3.1 Setting

In this section, we report the setting and results of our numerical calculations. Our calculations illustrate the implications of the theoretical model described in Sections 2.1 and 2.2 for our analysis of the effect of highway construction on worker residence and workplace choices in a metropolitan area. First, we report the setting of variables and exogenous parameters and then discuss the results of the numerical calculations.

We define the following three variables: final good productivity A_j, residential amenities B_i, and commuting cost k_{ij}. Final good productivity A_j has an exogenous component a_j, and an endogenous component, the agglomeration externality.[17] Following Ahlfeldt et al. (2015), we approximate the agglomeration externality using the following equation:

$$A_j = a_j \left[\sum_{j'}^{M} e^{-\rho_a \tau_{jj'}} \left(\frac{L_{j'}}{K_{j'}} \right) \right]^{\delta_a}, \tag{21}$$

where $L_{j'}/K_{j'}$ is workplace employment density per unit of land area. This type of agglomeration externality indicates that externality declines with the distance between cities through the iceberg factor $e^{-\rho_a \tau_{jj'}} \in (0, 1]$. In addition, ρ_a captures the rate of spatial decay, and δ_a indicates the relative importance of agglomeration externality in productivity.

Second, residential amenity B_i has an exogenous component b_j and an endogenous component. Following Ahlfeldt et al. (2015), we approximate the residential endogenous component as the number of residents using the following equation:

$$B_i = b_i \left[\sum_{i'}^{M} e^{-\rho_b \tau_{ii'}} \left(\frac{L_{i'}}{K_{i'}} \right) \right]^{\delta_b}, \tag{22}$$

where $L_{i'}/K_{i'}$ is residential density per unit of land area. This residential externality indicates that externality declines with the distance between cities through the iceberg factor $e^{-\rho_b \tau_{ii'}} \in (0, 1]$. In addition, ρ_b determines the rate of spatial decay, and δ_b captures the relative importance of overall residential amenities.

Next, the commuting cost is basically composed of commuting technology κ and travel distance τ,

$$k_{ij} = e^{\kappa \tau_{ij}}. \tag{23}$$

[17] The exogenous component a_j is approximated by access to natural water in Ahlfeldt et al. (2015).

Since we focus on the effect of highway construction, we assume two types of commuting technology: roads κ and highways κ_h. A highway connects the central city and a suburban city. According to Duranton and Turner (2011), highways are congested. Hence, we incorporate highway congestion into the model. When highways are constructed between a central city c and a suburban city s_f, the commuting cost from a suburban city f to a central city is

$$k_{s_f c} = e^{\left[\kappa_h + m(L_{s_f c} + L_{cc})\right]\tau_{s_f c}}, \tag{24}$$

where m captures the congestion cost.[18] In addition, assuming that the commuting cost in the central city is the average commuting cost of roads and highways, the commuting cost in the central city is

$$k_{cc} = e^{\left\{\left[(sub - n_h)\kappa + n_h(\kappa_h + m(L_{cc} + \sum_{i=1}^{\zeta} L_{cs_i} + L_{s_i c}))\right]/sub\right\}\tau_{cc}}, \tag{25}$$

where n_h captures the number of highway rays in the metropolitan area, sub indicates the number of suburban cities, and ζ includes cities that have highways; for example, if two highways connect c with s_1 and s_2, then $\zeta = \{1, 2\}$. Assuming that the commuting cost in the suburban city is the average commuting cost of roads and highways, the commuting cost in the suburban city is

$$k_{s_i s_i} = e^{\left\{\left[\kappa + (\kappa_k + mL_{s_i s_i})\right]/2\right\}\tau_{s_i s_i}}. \tag{26}$$

Next, we assume that the following equations describe the travel distance τ. If a worker chooses a residence and workplace in the same city, then $\tau_{ii} = 2/3\sqrt{K_i/\pi}$ approximates the travel distance, where K_i is the land area of i. Additionally, when a worker commutes to another city, we set $\tau_{s_i,c} < \tau_{c,s_i} < \tau_{s_i,s_j}$.

Numerical calculations require the following parameters: $\{\alpha, \beta, \delta_a, \delta_b, \rho_a, \rho_b, \mu, \epsilon, \kappa, \kappa_h, m\}$. Following Brinkman (2016) and Lucas and Rossi-Hansberg (2002), we set the share of goods in consumer expenditure α and labor in production costs β equal to 0.95 and 0.9, respectively. Referring to Ahlfeldt et al. (2015), we set the relative importance of agglomeration externality δ_a and spatial decay of agglomeration externality ρ_a equal to 0.08 and 0.35, respectively. In addition, we set the relative importance of residential externality δ_b and spatial decay of residential externality ρ_b equal to 0.15 and 0.75, respectively. According to Saiz (2010), we set the elasticity of the floor space supply μ and the constant parameter of floor supply d equal to 1.75 and 1, respectively. Commuting technology κ and κ_h equal 0.1 and 0.05, respectively[19]. Lastly,

[18] We follow Baum-Snow (2007b), Brinkman (2016), and Wheaton (2004) for this type of congestion cost.

[19] For the robustness check of this theoretical model, in Appendix A.3, we provide some numerical calculations

the dispersion of amenity ϵ equals 4.

Numerical calculations require the exogenous variables $\{\boldsymbol{K}, \boldsymbol{a}, \boldsymbol{b}, M, P, and \bar{U}\}$. We set the number of cities in metropolitan area M equal to 7: one central city and 6 suburban cities. In this setting, 6 highways can be constructed. Since the area of the central city is approximately 30 square miles and the metropolitan area was approximately $1,800$ square miles in US in 1950, we set $K_c = 30$ and $K_s = 300$.[20] Other exogenous parameters b_i and a_i are equal to unity. We assume $(\bar{U}/\eta)^\epsilon/\bar{L} = 1$, and the price of the final good is the numéraire, $P = 1$.

2.3.2 Results of the numerical calculation

Table 1 presents the results of numerical calculations that illustrate the theoretical model discussed in Section 2.1 and 2.2. The results of numerical calculations with congestion are in line with recent empirical papers; that is, employment and population decrease in central city relative to suburban cities as the number of highways increases.

The results imply that when commuters do not take congestion into account, employment in the central city increases relative to employment in suburban areas. On the other hand, employment in the central city decreases relative to that in suburban areas with congestion. The first low in the first column of Table 1 shows that central cities account for 63% of total employment in metropolitan areas with no highway rays. Without congestion, 68% of employment is concentrated in central areas when there are six highway rays. On the other hand, with high congestion cost ($m = 0.75$), only 54% of total employment is concentrated in central areas when there are six highway rays. In other words, employment in central cities decreases relative to employment in suburban areas with the construction of a highway. With a low congestion cost ($m = 0.2$), at first, the proportion of employment increases with an increase in the number of highways, and then, the proportion of employment decreases with an increase in the number of highways.

Regardless of congestion, population in central cities decreases relative to that in suburban areas. Without congestion, the effect of constructing highway rays on central city populations gradually increases. The entries in the second row in the first and second columns of Table 1 shows that the first highway ray decreases the proportion of the population in the central city by 4% and the last ray, from the fifth ray to the sixth ray, decreases the proportion of population in the central city by only 0.6%. On the other hand, with congestion ($m = 0.5$), the effect is

in which parameters are changed.

[20] The land area of the average metropolitan area is approximately 2,400 square miles, but Saiz (2010) indicates that only around 75% of the land area can be used for workers or firms.

a gradual increase. The entries in eighth row in the first and second columns indicate that the first ray decreases the proportion of the population in the central city by 1.4% and the last ray decreases the proportion of the central city population by 1.7%.

Moreover, regardless of congestion, total employment in metropolitan area, $\bar{L}$, increases with the number of highway rays. For instance, without congestion, the number of total employment increases from 0.08 to 0.25. On the other hand, with congestion ($m = 0.5$), the number of total employment increases from 0.08 to 0.15. The increase in total employment without congestion is larger than the increase in total employment with congestion.

The tendency of these three results from the theoretical model with congestion is in line with recent empirical analysis. First, employment in a central city is decentralized relative to employment in a suburban area. Baum-Snow (2010, 2019) shows that highway construction decreases central city employment in populated a metropolitan area. Second, population is also suburbanized. Baum-Snow (2007a) shows that highway rays cause suburbanization in the central city of a US metropolitan area. Finally, total employment increases, but congestion drags employment growth. According to Duranton and Turner (2012), highway construction fosters population and employment growth in US metropolitan areas, and Sweet (2014) indicates that a high level of congestion is associated with slower employment growth in US metropolitan areas.

2.3.3 Mechanism of suburbanization

This section discusses the mechanism of suburbanization. In particular, we ask: why do highways cause the suburbanization of employment and population? We focus on the difference between the results with congestion and those without congestion.

Table 2 shows the results of numerical calculations. Without congestion, the proportion of workers who live and work in a central city, λ_{cc}, decreases by 18%. The proportion of workers who live in a suburban city and work in a central city increases by 22% with an increase from zero to six rays. In addition, the proportion of workers who live and work in suburban cities decreases. These results imply that the mechanism of suburbanization without congestion is the same as that of the canonical urban model. Land rent in suburban areas is cheaper than land rent in a central city, and wages in a central city are higher than wages in suburban areas. When highways are constructed, workers can commute for longer distances. Hence, workers reside in suburban areas and commute to a central city to obtain higher wages and more floor space.

With congestion, the proportion of workers who live and work in a central city, λ_{cc}, decreases by 17%, and this result does not differ from the result without congestion. However, the propor-

Table 1: Results of numerical calculations

	Number of highway rays						
	0	1	2	3	4	5	6
$m = 0$ (No congestion)							
λ_c^L	0.631	0.649	0.660	0.668	0.674	0.679	0.683
λ_c^R	0.424	0.384	0.359	0.342	0.331	0.323	0.317
$\bar{L}$	0.083	0.108	0.135	0.162	0.191	0.221	0.252
$m = 0.2$							
λ_c^L	0.631	0.634	0.633	0.631	0.628	0.625	0.621
λ_c^R	0.424	0.398	0.379	0.364	0.352	0.340	0.330
$\bar{L}$	0.083	0.102	0.120	0.138	0.156	0.173	0.190
$m = 0.5$							
λ_c^L	0.631	0.620	0.607	0.596	0.585	0.575	0.567
λ_c^R	0.424	0.410	0.396	0.383	0.369	0.354	0.337
$\bar{L}$	0.083	0.096	0.107	0.118	0.129	0.139	0.150
$m = 0.75$							
λ_c^L	0.631	0.612	0.593	0.576	0.560	0.547	0.536
λ_c^R	0.424	0.415	0.405	0.393	0.378	0.361	0.340
$\bar{L}$	0.083	0.092	0.100	0.108	0.116	0.123	0.131

Note. λ_c^L and λ_c^R indicate the proportion of employment and residents in the central city, respectively. $\bar{L}$ shows the total employment in the metropolitan area.

Table 2: Mechanism of suburbanization

	Number of highway rays							
	0	1	2	3	4	5	6	Change
$m = 0$ (No congestion)								
λ_{cc}	0.405	0.341	0.300	0.271	0.252	0.237	0.226	-0.179
λ_{cs}	0.019	0.043	0.059	0.071	0.079	0.086	0.091	0.072
λ_{sc}	0.227	0.308	0.360	0.396	0.423	0.442	0.457	0.230
λ_{ss}	0.349	0.308	0.281	0.262	0.247	0.235	0.226	-0.123
$m = 0.5$								
λ_{cc}	0.405	0.369	0.338	0.310	0.283	0.257	0.231	-0.175
λ_{cs}	0.019	0.041	0.059	0.073	0.086	0.097	0.107	0.088
λ_{sc}	0.227	0.251	0.270	0.286	0.302	0.318	0.337	0.110
λ_{ss}	0.349	0.339	0.326	0.334	0.331	0.329	0.328	-0.023
$m = 0.75$								
λ_{cc}	0.405	0.376	0.348	0.332	0.293	0.263	0.233	-0.172
λ_{cs}	0.019	0.040	0.057	0.072	0.085	0.097	0.107	0.088
λ_{sc}	0.227	0.236	0.245	0.255	0.267	0.283	0.303	0.077
λ_{ss}	0.349	0.348	0.350	0.352	0.355	0.356	0.356	0.007

Note. λ_{cc}, λ_{cs}, λ_{sc}, and λ_{ss} indicate the proportion of workers who live and work in central cities, live in central cities and work in suburban cities, live in suburban cities and work in central cities, and live and work in suburban cities, respectively.

tion of workers who live and work in suburban cities, λ_{ss}, increases by 0.7%, and the proportion of workers who live in suburban areas and work in central cities, λ_{sc}, increases by 7%, but the growth rate is smaller than the results without congestion. These results imply the mechanism of suburbanization in a theoretical model with congestion. Congestion functions as dispersion when high costs for commuting within a central city and into a central city from suburban areas make the dispersion force in a central city strong when a highway is constructed in the central city. Although the wages in central cities are high, workers do not have any incentive to work in a central city because of the high commuting costs. In addition, land rent in a central city is higher than that in suburban cities. Therefore, workers move to and work in suburban cities to avoid high commuting costs and land rent.

2.4 To guide our empirical analysis

The results of our numerical calculations are in line with the results of recent empirical studies. In addition, we provide additional evidence to examine the validity of our theoretical model.

Table 3 shows the effect of additional highways on central city populations. We calculate

Table 3: The effect of change in the number of highways

	Change in the number of highways					
	0 - 1	1 - 2	2 - 3	3 - 4	4 - 5	5 - 6
$m = 0$	-0.043	-0.029	-0.021	-0.015	-0.010	-0.007
$m = 0.2$	-0.028	-0.021	-0.017	-0.015	-0.014	-0.014
$m = 0.5$	-0.015	-0.014	-0.015	-0.016	-0.018	-0.021
$m = 0.75$	-0.009	-0.011	-0.013	-0.017	-0.021	-0.025

Note. Each entry shows the results of $\Delta \log \mathrm{CCpop} - \Delta \log \bar{L}$. These entries show the effect of change in the number of highways on central city populations considering the change in total employment.

this effect by $\Delta \log \mathrm{CCpop} - \Delta \log \bar{L}$, where $\Delta \log \mathrm{CCpop} = \log \mathrm{CCpop}_{n_h+1} - \log \mathrm{CCpop}_{n_h}$ indicates the central city population growth with one additional highway ray, and to consider total employment growth in metropolitan areas, we use $\Delta \bar{L}$.[21] Without congestion, the effect is gradually decreasing. For instance, the first row of the first column is -0.043, and the fifth column is approximately -0.007. This result implies that the relationship between the number of highway rays and the reduction in the number of residents in the central city is convex and monotone decreasing.

On the other hand, when commuters take congestion into account, the relationship is only monotone decreasing. For example, the first column in the third row is -0.015, the next column is -0.014, and the fifth column is -0.021. This result indicates that the relationship between the number of highway rays and the reduction in the number of residents in the central city is monotone decreasing. We focus on this difference in the empirical analysis.

One possible reason for interpreting these differences is that a reduction in commuting costs without congestion is effectively an increase in income. If income increases at a fixed rate due to a decrease in commuting costs, then the effect gradually decreases under the assumption that the utility function is a quasi-concave function. On the other hand, when workers take congestion into account, commuting costs will not decrease in the central city by highway construction; instead, the dispersion force induced by congestion increases. Further, as the number of highways passing through the central city increases, the dispersion force in the central city increases, and thus the relationship between highway construction and change in central city population becomes only monotone decreasing.

[21] CCpop indicates the central city population.

3 Data and Estimation Methodology

In Section 2, we provide the numerical simulation with and without congestion to explain the mechanism of suburbanization, specifically, how highway congestion affects suburbanization. Thus, we focus on the difference between the theoretical model with and without highway congestion to identify the mechanism of suburbanization. We use partial identification to identify the mechanism. Partial identification obtains a bound with an assumption and the estimated bound indicates the range of causal effect under the assumption. Here, we draw the assumption from the results of the numerical calculations. The numerical calculation results for the theoretical model without congestion imply that increasing the number of highway rays in a metropolitan area decreases the central city population, and this relationship is convex and monotone decreasing. On the other hand, the numerical calculation results for the theoretical model with congestion also imply the relationship is just monotone decreasing. We focus on this difference to identify the mechanism. The following section explains the data and how we estimate the bound with the assumptions of monotone decreasing and convex monotone decreasing relationships.

3.1 Data and interstate highway system

Our unit of observation is a central city in a metropolitan area in US constructed by the 1950 boundary. The metropolitan statistical area (henceforth referred to as the MSA) was defined by the Office of Management and Budget in 2000, and we define it as the metropolitan area. The city that has the largest population size in the MSA is the central city. The data set is the same as that in Baum-Snow (2007a).[22] In addition, Baum-Snow (2007a) states that the data for counties and cities are from the *County and City Data Books*. Our main variables are change in central city population from 1950 to 1990, and the highway construction in the metropolitan area.[23]

In this paper, the key aspect is the construction of interstate highway rays. *Rays* are defined as the number of highways that connect the central city and suburban city, and must pass within one mile of the central city. We also include limited-access express ways, which satisfy the *rays'* conditions. For instance, when a highway passes through the central city, there are two rays in this central city. These data come from the *Road Atlas* and *The Form PR-551 Database*.

The construction of the interstate highway system is not an exogenous event. Therefore, we

[22]These data are generously shared by Nathaniel Baum-Snow.
[23]See Appendix D for descriptive statistics.

employ the 1947 plan for the interstate highway system as the instrumental variable. This plan is good for IV because of following reasons. In 1938, Franklin D. Roosevelt made a plan for the interstate highway system, and in 1940's, based on the Roosevelt plan, a plan for the interstate highway system was suggested, themed *Interregional Highways*. This plan was considered during the Second World War, and hence it considers the location of military establishments, interregional traffic demand, and distribution of the population at the time. In 1956, the construction of the interstate highway began, with the federal government paying for highway construction. However, in some metropolitan areas, the cost of highway construction was covered by local instead of federal governments and some highways were constructed to improve commuting; thus, this deviation from 1947 plan works as the exogenous variation of the actual highway construction. Baum-Snow (2007a), and Duranton and Turner (2011, 2012) employ the 1940s plans as the instrumental variable for highway construction. We also check the validity of the 1947 plan for the instrumental variable and report the results in Appendix C. The result implies that the instrumental variable is a strong predictor of the number of highway rays in the MSA.

3.2 Estimation methodology

3.2.1 Basic setup

The basic setup of this estimation methodology follows Manski (1997). Each city, j, has a response function $p_j(\cdot) : T \to P$, mapping treatment $t \in T = \{1, 2, 3, 4, 5, 6\}$ into outcomes $p_j(t) \in P$.[24] t indicates the number of highway rays, and $p_j(t)$ is the change in the log population in the constant geography of the central city, j, from 1950 to 1990 with treatment t. Each city, j, has a realized treatment, $z_j \in T$, and a realized outcome, $p_j \equiv p_j(z_j)$. The realized treatment is the number of rays in 1990. In addition, each city, j, has covariates $v_j \in T$. v_j, z_j, and p_j are observable. The latent outcomes, $p_j(t), t \neq z$, are not observable.

3.2.2 Monotone decreasing

According to theoretical models, regardless of highway congestion, the relationship between the change in log population and treatment (the number of highway rays) is monotone decreasing. Hence, we first explain how to estimate the bound with the assumption of this relationship,

[24] This estimation methodology requires the conditions of $P = [0, \infty]$ and $T = [0, \theta]$ for some $\theta = (0, \infty]$. Because of this condition, p_j equals the maximum change in the log population—the change in the log population in city j and number of highway rays plus one. Additionally, there are few cities for which the number of highways is more than six. Hence, $z_j = 6$ when the number of highways is more than five. The planned highway rays are sifted using the same method as the number of highway rays.

which we represent as

$$t \geq s \Rightarrow p_j(t) \leq p_j(s)$$

for all $j \in J$, $t \in T$, and $s \in T$. Under this assumption, Manski (1997) suggests that the sharp bounds on $E[p(t)]$ are

$$\begin{aligned} &\sum_{t \leq s} E[p|z = s] \Pr(z = s) + p_0 \Pr(z < t) \\ &\leq E[p(t)] \leq \\ &p_1 \Pr(z > t) + \sum_{s \leq t} E[p|z = s] \Pr(z = s), \end{aligned} \tag{27}$$

where $[p_0, p_1]$ is the range of p_j.[25] The sharp bounds on the average treatment effect of $E[p(t_2)] - E[p(t_1)]$ are the lower bound of $E[p(t_2)]$ minus the upper bound of $E[p(t_1)]$; in other words, the sharp bounds on the average treatment effect $E[p(t_2)] - E[p(t_1)]$ are

$$\begin{aligned} &\left[p_0 P(z > t_2) + \sum_{s \leq t_2} E[p|z = s] \Pr(z = s) \right. \\ &\left. - \sum_{s \leq t_1} E[p|z = s] \Pr(z = s) + p_1 \Pr(z < t) \right] / (t_2 - t_1) \\ &\leq \{E[p(t_2)] - E[p(t_1)]\}/(t_2 - t_1) \leq 0 \quad , \end{aligned} \tag{28}$$

where $t_2 > t_1$.

We assume that the covariate, v, is an instrumental variable. According to Manski and Pepper (2000), the assumptions of the instrumental variables must satisfy the following condition:

$$E[p(t)|v = u_1] = E[p(t)|v = u_2] = E[p(t)], \tag{29}$$

where $u_1 \in T$ and $u_2 \in T$. As we discussed in Section 3.1, the instrumental variable could be considered to hold assumption (29). Under the condition of the instrumental variable, the sharp

[25] The sharp bounds are defined as the narrowest of the bounds of data distribution and the assumptions.

bounds on $E[p(t)]$ with the instrumental variable are

$$\max_{u\in V}\left\{\sum_{t\leq s} E[p|z=s,v=u]\Pr(z=s|v=u)+p_0\Pr(z<t|v=u)\right\}$$
$$\leq E[p(t)]\leq \tag{30}$$
$$\min_{u\in V}\left\{p_1\Pr(z>t|v=u)+\sum_{s\leq t} E[p|z=s,v=u]\Pr(z=s|v=u)\right\}.$$

Moreover, the sharp bounds on the average treatment effect $E[p(t_2)] - E[p(t_1)]$ with the instrumental variable are

$$\left[\max_{u\in V}\left\{\sum_{t_2\leq s} E[p|z=s,v=u]\Pr(z=s|v=u)+p_0\Pr(z<t_2|v=u)\right\}\right.$$
$$\left.-\min_{u\in V}\left\{p_1\Pr(z>t_1|v=u)+\sum_{s\leq t_1} E[p|z=s,v=u]\Pr(z=s|v=u)\right\}\right]/(t_2-t_1) \tag{31}$$
$$\leq \{E[p(t_2)]-E[p(t_1)]\}/(t_2-t_1)\leq 0.$$

3.2.3 Convex monotone decreasing

The theoretical model without highway congestion implies that an increase in the number of highway rays causes a reduction in the population in the central city, and this relationship is convex and monotone decreasing. Hence, we impose this relationship on the data to examine the validity of the theoretical model without highway congestion.[26] The sharp bound of $E[p(t)]$ is

$$\sum_{s\leq t} E[p|z=s]\Pr(z=s)+\sum_{s>t} E\left[\frac{p}{s}\,t\;\middle|\; z=s\right]\Pr(z=s)$$
$$\leq E[p(t)]\leq \tag{32}$$
$$\sum_{s<t} E\left[\frac{p}{s}\,t\;\middle|\; z=s\right]\Pr(z=s)+\sum_{s\geq t} E[p|z=s]\Pr(z=s).$$

[26] Manski (1997) suggests the bound estimation with the assumption of a convex and monotone decreasing response.

According to Manski (1997), the sharp bound of the average treatment effect $E[p(t_2)] - E[p(t_1)]$ is

$$
\begin{aligned}
&\left[\sum_{s \le t_2} E\left[\frac{p}{t_2} \;\middle|\; z = s\right](t_2 - t_1)\Pr(z = s)\right. \\
&\left. + \sum_{s < t_2} E\left[\frac{p}{z} \;\middle|\; z = s\right](t_2 - t_1)\Pr(z = s)\right] / (t_2 - t_1) \\
&\le E[p(t_2)] - E[p(t_1)] \le 0.
\end{aligned} \tag{33}
$$

We introduce the covariate, v, as an instrumental variable. Under the assumption of the instrumental variable (29), the sharp bound on $E[p(t)]$ is

$$
\begin{aligned}
&\max_{u \in V}\left\{\sum_{s \le t} E[p|z = s, v = u]\Pr(z = s|v = u) + \sum_{s > t} E\left[\frac{p}{s}\, t \;\middle|\; z = s, v = u\right]\Pr(z = s|v = u)\right\} \\
&\le E[p(t)] \le \\
&\min_{u \in V}\left\{\sum_{s < t} E\left[\frac{p}{s}\, t \;\middle|\; z = s, v = u\right]\Pr(z = s|v = u) + \sum_{s \ge t} E[p|z = s, v = u]\Pr(z = s|v = u)\right\}.
\end{aligned} \tag{34}
$$

In addition, the sharp bound on the average treatment effect $E[p(t_2)] - E[p(t_1)]$ with the assumption of the instrumental variable and the convex monotone decreasing response function is

$$
\begin{aligned}
&\max_{u \in V}\left\{\left[\sum_{s \le t_2} E\left[\frac{p}{t_2} \;\middle|\; z = s,\ v = u\right](t_2 - t_1)\Pr(z = s \mid v = u)\right.\right. \\
&\left.\left. + \sum_{s < t_2} E\left[\frac{p}{z} \;\middle|\; z = s,\ v = u\right](t_2 - t_1)\Pr(z = s \mid v = u)\right] / (t_2 - t_1)\right\} \\
&\le \{E[p(t_2)] - E[p(t_1)]\} / (t_2 - t_1) \le 0.
\end{aligned} \tag{35}
$$

Imbens and Manski (2004) and Manski and Pepper (2009) show that there is a finite sample bias when we use the instrumental variable. Specifically, (30), (31), (34), and (35) may have a finite sample bias. Chernozhukov et al. (2013) suggest median unbiased estimators and confidence intervals of the bounds, and they provide a formal justification of their estimators by asymptotic theory.[27]

[27] See appendix B for details on Chernozhukov et al. (2013)'s estimation methodology.

4 Empirical Analysis

Our partial identification has two types of assumptions: monotone decreasing and convex monotone decreasing. According to the theoretical model in Section 2, when we do not consider highway congestion, the relationship between the increase in the number of highway rays and the decrease in log population of the central city is convex and monotone decreasing. The relationship becomes only monotone decreasing when we account for highway congestion. We examine these implications in Section 2 by partial identification. The assumption of a monotone decreasing relationship corresponds to the theoretical model regardless of highway congestion, whereas the other assumption of a convex monotone decreasing relationship corresponds to the theoretical model without highway congestion. These estimated bounds indicate the range of the average causal effect of one new highway ray on the population of its central city under these assumptions.

On the other hand, the point estimates obtained by the instrumental variable indicate the average effect of one new highway ray on the population of a central city, which is the causal effect. These point estimates enable us to examine the implications of the theoretical models, specifically, how highway congestion affects the mechanism of suburbanization. If the point estimates are outside of the bound estimated with the assumption of convex and monotone decreasing, then the theoretical model without congestion is not evidenced by the data. On the other hand, when the point estimates are inside the bound estimates with the assumption of convex and monotone decreasing, both the theoretical models (i.e., with and without congestion) are evidenced by the data. In addition, the theoretical model with congestion is evidenced by the data when the point estimates are inside the bound estimates with the assumption of monotone decreasing and outside the bound estimates with the assumption of convex and monotone decreasing.

We use five data sets for metropolitan cities in US: (1) data for the MSA in 2000, (2) data on cities with a central city population of at least 50,000 in 1950, (3) data on cities with a central city population above 75,000 in 1950, (4) data on cities in which the MSA population was larger than 100,000 in 1950, and (5) data on cities with a central city population larger than 50,000 and an MSA population larger than 100,000 in 1950.

4.1 Empirical analysis results

In this section, we report the results of the empirical analysis, which involved two types of estimates: point estimates obtained by the instrumental variable method and bound estimates obtained by partial identification. We first estimate the following equation with the instrumental variable of the 1947 planned route to obtain the point estimates of the treatment effect:[28]

$$p_j = \beta_0 + \beta_1 z_j + \boldsymbol{\beta X} + \varepsilon_j, \tag{36}$$

where β_1 shows the average treatment effect; that is, the marginal effect of highway rays on p_j. $\boldsymbol{X}$ are the other explanatory variables. The entries in Panel A of Table 4 represent the coefficient on z_j; that is, β_1. In addition, we have five explanatory variables, following Baum-Snow (2007a). We include the square root of the 1950 central city area as a control in specifications (i) to (v). We add the change in simulated log income to specifications (ii) to (v) and the change in the log MSA population in specifications (iii) to (v). We introduce the change in the Gini coefficient in specifications (iv) and the log 1950 MSA population in specification (v).[29] The entries in Panel B of Table 4 represent the bound estimates. (vi) and (vii) show the bound estimates derived with the assumption of a monotone decreasing and convex monotone decreasing relationship with the instrumental variable, respectively.

The results in Panel A show the marginal effect of highway construction on central city population. We find that all point estimates show negative coefficients and they are around -10%. Moreover, they are similar to Baum-Snow (2007)'s results. The result in the fifth row of the first column indicates that one additional highway ray decreases the central city population of the MSA by approximately 11%.

Table 4 presents two noteworthy features. First, the data on all cities with metropolitan areas in US support the theoretical model with highway congestion. Entries in the sixth row of Panel B are the results of the bound estimation with the assumptions of monotone decreasing and the instrumental variable. These results indicate the bound of the causal effect with the assumptions; for instance, the result in the first column shows that the marginal effect of highway construction on central city population is at most -0.33 when we assume the relationship between highway rays and central city population is monotone decreasing. In other words, an additional highway ray decreases the central city population from -33% to 0%. The other columns contain similar results. All of the point estimates are in the bound with the assumption of a monotone

[28]The background of this estimation equation and the results of first stage are given in Appendix C.
[29]The estimates of equation (36) are given in Appendix C.

decreasing relationship.

Second, the theoretical model without congestion is not evidenced by the data on populated cities in 1950. Entries in the seventh row of Panel B present the results of the bound estimation with the assumptions of convex, monotone decreasing, and instrumental variables. The results become narrower than the results in the sixth row because of the difference in assumptions. The results imply that the point estimates of cities that had a large population in 1950 tend to be outside of the bound estimates. For example, the second column of Table 4, which includes cities that had a large population in 1950, shows that the point estimates are at least -0.099. However, the bound estimate with the assumption of a convex monotone decreasing relationship is between -0.088 and 0, that is, point estimates are outside of the bound with assumptions related to the theoretical model without congestion. In addition, the third column of Table 4, which also includes cities that had a larger population in 1950, shows a similar result. By theoretical prediction, the bound estimates indicate that the point estimates should be between -0.065 and 0. However, the point estimates are approximately -0.125. Hence, they are not within the bound estimates. Column 5 shows similar results. According to Section 2, the mechanism of suburbanization in theoretical model without congestion is the same as canonical urban models. Therefore, these results imply that canonical urban models are not evidenced by the data on populated cities.

4.2 Robustness check

4.2.1 Congestion index

Our theoretical model implies that congestion in a central city is the causative factor in the relationship between highway construction and both employment and population decentralization. As a robustness check, we use the $(number\ of\ highway\ rays\ ) + 1/population$ ratio (henceforth, h/p). When the h/p ratio is high, there are fewer people on highways; in other words, the city is less congested. On the other hand, when this ratio is low, there is congestion on the city's highways.

The results in Table 5 allow us to understand whether the findings in Section 4.1 are robust, that is, whether central city congestion is important for the mechanism of suburbanization.

The first two columns use the population data for the central city populations in 1990. Column 1 uses data on cities with a h/p ratio below the median, and the second column uses data on cities whose h/p ratio is below the quartile (75^{th} percentile). All point estimates in the first column (below the median) are significant and at most -0.113, in other words, one

Table 4: Point and bound estimation results

	1. All MSA in 2000	2. CC pop. > 50k in 1950	3. CC pop. > 75k in 1950	4. MA pop. > 100k in 1950	5. CC pop. > 50k & MSA pop. > 100k in 1950
			Panel A: Point estimation		
(i)	-0.090***	-0.108***	-0.128***	-0.105***	-0.112***
	(-3.44)	(-3.34)	(-2.47)	(-3.10)	(-3.11)
(ii)	-0.078***	-0.113***	-0.130***	-0.098***	-0.118***
	(-3.26)	(-3.39)	(-2.63)	(-3.15)	(-3.23)
(iii)	-0.133***	-0.130***	-0.139***	-0.137***	-0.128***
	(-4.27)	(-4.03)	(-3.49)	(-3.65)	(-3.77)
(iv)	-0.131***	-0.120***	-0.125***	-0.118***	-0.117***
	(-4.41)	(-4.08)	(-3.80)	(-3.64)	(-3.99)
(v)	-0.109**	-0.099*	-0.122**	-0.122**	-0.106*
	(-2.07)	(-1.92)	(-2.13)	(-2.15)	(-1.98)
			Panel B: Bound estimation		
(vi)	[-0.328, 0]	[-0.217, 0]	[-0.260, 0]	[-0.361, 0]	[-0.239, 0]
C. I.	[-0.333, 0]	[-0.223, 0]	[-0.267, 0]	[-0.370, 0]	[-0.245, 0]
(vii)	[-0.172, 0]	[-0.088, 0]	[-0.065, 0]	[-0.145, 0]	[-0.086, 0]
C. I.	[-0.175, 0]	[-0.090, 0]	[-0.066, 0]	[-0.147, 0]	[-0.090, 0]
No. Obs.	240	151	111	165	139

Note. We used five data sets: 1. Data on metropolitan statistical areas (MSAs) in 2000, 2. Data on cities whose central city (CC in the table) populations were at least 50,000 in 1950, 3. Data on cities with central city populations larger than 75,000 in 1950, 4. Data on cities with an metropolitan area (MA) population larger than 100,000 in 1950, and 5. Data on cities with a central city population larger than 50,000 and an MSA population larger than 100,000 in 1950.

Panel A shows the results of the point estimation, in which the entries represent the coefficients on z_j; that is, β_1, in (36). The standard errors are clustered by the state of the MSA city. With this standard error, we provide the t-values in parentheses, and ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All estimations in Panel A use the number of highway rays in the 1947 plan as the instrumental variable. We include the square root of the 1950 central city area as a control in specifications (i) to (v). We add the change in simulated log income in specifications (ii) to (v), change in the log MSA population in specifications (iii) to (v), change in the Gini coefficient in specifications (iv), and the log 1950 MSA population in specification (v).

Panel B reports the partial identification results. (vi) and (vii) show the results of the partial identification estimated with the assumption of a monotone decreasing function and convex monotone decreasing function with the instrumental variable, respectively.

additional highway ray decreases the central city population by 11.3%. Bound estimates with the assumption related to our theoretical model (with congestion) are between -0.108 and 0, and some point estimates are inside the bound. The confidence interval is between -0.113 and 0, hence, our theoretical model is partially evidenced by the data. On the other hand, bound estimates with the assumption related to the canonical urban model are between -0.098 and 0, and all point estimates are outside the bound. These results imply that the theoretical model with congestion is evidenced by data on congested central cities, and the theoretical model without congestion is not evidenced.

Column 2 indicates that both theories are partially evidenced by data on a less congested central city. Point estimates in the second column are also significant, and at least -0.086. Both bound estimates include some point estimates. For instance, the bound estimate with the assumption of monotone decreasing (an entry in the sixth row) is between -0.189 and 0, and the point estimates are inside the bound. In addition, the bound estimate with the assumption of convex and monotone decreasing is between -0.116 and 0, and some point estimates are inside the bound.

On the other hand, the last two columns use the population data for metropolitan area populations in 1990 to check whether congestion in the metropolitan area is important. The second-last column uses data on cities with a h/p ratio below the median, and the last column uses data on cities with a h/p ratio below the quartile. All point estimates in the third column (below median) are significant and are at most -0.107 and at least -0.079. Bound estimates with the assumption of our theoretical model (with congestion) are between -0.159 and 0, and all point estimates are inside the bound. In addition, bound estimates with the assumption of the canonical urban model are between -0.108 and 0, and all point estimates are also inside the bound. These results imply that metropolitan area congestion is not important for the mechanism of suburbanization.

4.2.2 Potential endogeneity

According to Duranton and Turner (2012), highway construction fosters metropolitan area population growth. Taking this potential endogeneity problem into account, we used national population growth from 1950 to 1990 excluding metropolitan area population growth as the other instrumental variable in specifications (viii) to (xi).[30] We included the change in the log MSA

[30] This instrumental variable is referred to in Garcia-López et al. (2015). The results of the first stage are in Appendix C .

Table 5: Robustness check for congestion

	h/p ratio in CC		h/p ratio in MA	
	below median	below quartile	below median	below quartile
	Panel A: Point estimation			
(i)	-0.093***	-0.092***	-0.079***	-0.105***
	(-3.79)	(-4.45)	(-3.20)	(-3.60)
(ii)	-0.090***	-0.086***	-0.076***	-0.094***
	(-3.57)	(-4.05)	(-2.98)	(-3.42)
(iii)	-0.112***	-0.121***	-0.104***	-0.136***
	(-4.48)	(-5.14)	(-3.98)	(-3.93)
(iv)	-0.109***	-0.123***	-0.100***	-0.132***
	(-4.24)	(-4.99)	(-3.71)	(-4.03)
(v)	-0.113***	-0.092**	-0.107**	-0.175**
	(-3.01)	(-2.57)	(-2.43)	(-2.21)
	Panel B: Bound estimation			
(vi)	[-0.108, 0]	[-0.189, 0]	[-0.159, 0]	[-0.225, 0]
C. I.	[-0.113, 0]	[-0.194, 0]	[-0.166, 0]	[-0.229, 0]
(vii)	[-0.098, 0]	[-0.116, 0]	[-0.108, 0]	[-0.117, 0]
C. I.	[-0.099, 0]	[-0.119, 0]	[-0.110, 0]	[-0.120, 0]
No.obs	119	180	113	179

Note. We use the highway/population (h/p) ratio. The first two columns use the population data for central city (CC in the table) populations in 1990. The last two columns use the population data for metropolitan area (MA in the table) populations in 1990.

Panel A shows the results of point estimation, in which the entries represent the coefficients on z_j; that is, β_1, in (36). The standard errors are clustered by the state of the metropolitan statistical area (MSA) city. With this standard error, we provide the t-values in parentheses, and ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All estimations in Panel A use the number of highway rays in the 1947 plan as the instrumental variable.

Panel B reports the partial identification results. (vi) and (vii) show the results of the partial identification estimated with the assumption of a monotone decreasing function and convex monotone decreasing function with the instrumental variable, respectively.

population in specifications (viii) to (xi), the change in the Gini coefficient in specifications (ix), and the log of the 1950 MSA population in specification (x). In addition, Baum-Snow et al. (2017) indicate that the log of the 1950 MSA population also has potential endogeneity. Hence, the log of the 1950 MSA population turns into the log of the 1940 MSA population in specifications (xi) and (xii).[31]

Panel A in Table 6 shows the results of a robustness check for the potential endogeneity problem. Even though the results of point estimation are a little smaller than the main results in Table 4, all bound estimates with the assumption of monotone decreasing include point estimates, that is, our theoretical model is evidenced by the data. Point estimates in the second, third, and fifth columns are outside of the bound with the assumptions of convex and monotone decreasing. In other words, our main findings—that our theoretical model is evidenced by data on all US metropolitan areas, and the canonical urban model is not evidenced by data on congested central cities in 1950—remain unchanged.

5 Conclusion

In sum, this paper presents theoretical and empirical evidence that how commuting congestion induced by highway construction affect the distribution of employment and population in metropolitan areas. First, we develop a spatial equilibrium model of urban land use with highway congestion to examine the effect of congestion on the distributions of population and employment. The results of numerical simulation with congestion indicated that population and employment are decentralized by highway construction—these results were in line with recent empirical evidence. Meanwhile, we ran a theoretical model without congestion (related to canonical urban model) and found that, within this model, highway construction suburbanizes population, but centralizes employment.

Next, we examine the validity of our model with congestion, in other words, we look to see if congestion impacted workers' residential and workplace decisions. The implications of the two theoretical models with and without congestion prove to be the same: in both, the population in the central city decreased with highway construction, but the mechanisms of suburbanization differs. Consequently, the difference between the mechanisms is rooted in the relationship between highway construction and population decline, and we thus focus on that. The result of numerical calculation using the theoretical model without highway congestion implies that

[31]Baum-Snow et al. (2017) indicate that past population reduces the possibility of potential endogeneity.

Table 6: Robustness check for the endogeneity problem

	1. All MSA in 2000	2. CC pop. > 50k in 1950	3. CC pop. > 75k in 1950	4. MA pop. > 100k in 1950	5. CC pop. > 50k & MA pop. > 100k in 1950
			Panel A: Point estimation		
(viii)	-0.138***	-0.133***	-0.140***	-0.142***	-0.131***
	(-4.26)	(-4.17)	(-3.58)	(-3.81)	(-3.89)
(ix)	-0.136***	-0.127***	-0.129***	-0.129***	-0.127***
	(-4.39)	(-4.32)	(-3.95)	(-3.99)	(-4.17)
(x)	-0.113*	-0.099*	-0.122**	-0.127**	-0.107*
	(-1.85)	(-1.89)	(-2.10)	(-2.13)	(-2.01)
(xi)	-0.107**	-0.095*	-0.117*	-0.115**	-0.103*
	(-2.04)	(-1.70)	(-1.81)	(-2.05)	(-1.83)
(xii)	-0.113*	-0.093*	-0.117*	-0.121*	-0.099*
	(-1.72)	(-1.82)	(-1.96)	(-1.96)	(-1.85)
			Panel B: Bound estimation		
(vi)	[-0.328, 0]	[-0.217, 0]	[-0.260, 0]	[-0.361, 0]	[-0.239, 0]
C. I.	[-0.333, 0]	[-0.223, 0]	[-0.267, 0]	[-0.370, 0]	[-0.245, 0]
(vii)	[-0.172, 0]	[-0.088, 0]	[-0.065, 0]	[-0.145, 0]	[-0.086, 0]
C. I.	[-0.175, 0]	[-0.090, 0]	[-0.066, 0]	[-0.147, 0]	[-0.090, 0]
No. Obs.	240	151	111	165	139

Note. Panel A shows the results of point estimation for which the entries represent the coefficients on z_j; that is, β_1, in (36). The standard errors are clustered by the state of the metropolitan statistical area (MSA) city. With this standard error, we provide the t-values in parentheses, and ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. We include the change in the log MSA population in specifications (viii) to (xi), the change in the Gini coefficient in specifications (ix), and the log of the 1950 MSA population in specification (x). We add national population growth excluding the metropolitan area as an instrumental variable in specifications (viii) to (xi). In addition, we use the log of the 1940 MSA population instead of the log of the 1950 MSA population in specifications (xi) and (xii). Data sets and Panel B are the same as in Table 4 increasing the number of highway rays in a metropolitan area causes the central city's population to decrease, and this relationship is convex and monotone decreasing. On the other hand, the result of numerical calculations using theoretical model with highway congestion imply this relationship is only monotone decreasing. Focusing on the difference in this relationship, we use partial identification to examine the validity of our theoretical model. The empirical analysis results imply that the data on all central cities of MSA in US support the theoretical model with congestion. Meanwhile, the empirical analysis indicated that the data on cities with a large population in the central city in 1950 do not support the theoretical model without congestion. The deeper point here is that our theoretical model is thus valid and therefore should prove helpful for designing policies with careful consideration of severe traffic congestion in metropolitan areas, such as those related to local taxation, zoning, and transportation infrastructure.

One issue remains outstanding and requires the attention of future researchers. This paper focuses on vehicle congestion, and this type of congestion increases commuting time by increasing waiting time or in-vehicle time. Since many US workers use their own cars and highways to commute, our theoretical and empirical evidence were applied to US metropolitan areas. However, in the European or Japanese metropolitan area, workers usually use public transportation systems. According to Tirachini et al. (2013) and de Palma et al. (2017), congestion related to public transportation, such as railroad congestion, causes stress and feelings of exhaustion, but does not affect commuting time. In observing employment and population decentralization in large metropolitan areas such as Paris (Mayer and Trevien, 2017), there is a possibility that feelings of exhaustion—alongside long commuting time—may affect suburbanization. Future scholars may thus employ data on cities in other metropolitan areas such as those in the EU or Japan to answer the following remaining question: do all types of commuting congestion cause suburbanization?

Appendix

A Theoretical model appendix

A.1 Residence and workplace choices

From (7), we represent the indirect utility as

$$U = \frac{b_{ijo} w_j}{P_i^{\alpha} Q_i^{1-\alpha} k_{ij}}. \tag{A.1}$$

We assume that the idiosyncratic amenity shock b_{ijo} follows a Fréchet distribution. The distribution of the utility for worker o residing in i and working in j also follows a Fréchet distribution:

$$G_{ij}(u) = e^{-\psi_{ij} U^{-\epsilon}}, \tag{A.2}$$

where $\psi_{ij} = B_i \left(P_i^{\alpha} Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^{\epsilon}$. Since the maximum of a sequence of Fréchet-distributed random variables is itself Fréchet distributed, the distribution of utility across all possible pairs of residence and employment areas is

$$1 - G(u) = 1 - \prod_r \prod_t e^{-\psi_{rt} u^{-\epsilon}} \tag{A.3}$$

where the left-hand side indicates that a worker has a utility greater than u, and the right-hand side is one minus the probability that the worker has a utility less than u for all possible pairs of residence and employment areas. This implies that

$$G(u) = e^{-\psi_{rt} u^{-\epsilon}} \tag{A.4}$$

where $\psi = \sum_r \sum_t \psi_{rt}$. Given the Fréchet distribution for utility, the expected utility is

$$\mathbb{E}[u] = \int_0^{\infty} \epsilon \psi u^{-\epsilon} e^{-\psi u^{-\epsilon}} du. \tag{A.5}$$

We define the following change in variables, $y = \psi u^{-\epsilon}$. Hence, we obtain $dy = -\epsilon \psi u^{-(\epsilon+1)}$. Using the change in variables, we can rewrite the expected utility as

$$\mathbb{E}[u] = \int_0^{\infty} \psi^{1/\epsilon} y^{-1/\epsilon} e^{-y} dy. \tag{A.6}$$

Now, we define η as

$$\eta = \Gamma\left(\frac{\epsilon - 1}{\epsilon}\right) \tag{A.7}$$

where $\Gamma(.)$ is the Gamma function. Therefore, the expected utility function is

$$\mathbb{E}[u] = \eta\psi^{1/\epsilon}, \tag{A.8}$$

using the expression in the paper is

$$\begin{aligned} \bar{U} :=& \mathbb{E}[u] \\ =& \eta\left[\sum_r^M \sum_t^M B_r \left(P_r^\alpha Q_r^{1-\alpha} k_{ij}\right)^{-\epsilon} w_t^\epsilon\right]^{1/\epsilon}. \end{aligned} \tag{A.9}$$

We now explain the choices of residence and workplace. The probability that a worker chooses area i as a residence and area j as a workplace, λ_{ij}, is

$$\begin{aligned} \lambda_{ij} &= \Pr[u_{ij} \geq \max\{u_{rt}\} \;\; \forall\, r, t] \\ &= \int_0^\infty \prod_{t \neq j} G_{it}(u) \left[\prod_{r \neq i} \prod_t G_{rt}(u)\right] g_{ij}(u) du \\ &= \int_0^\infty \prod_r \prod_t \epsilon\psi_{ij} u^{-(\epsilon+1)} e^{-\psi_{rt} u^{-\epsilon}} du \\ &= \int_0^\infty \epsilon\psi_{ij} u^{-(\epsilon+1)} e^{-\psi u^{-\epsilon}} du. \end{aligned} \tag{A.10}$$

Using this result, we can rewrite the probability that a worker chooses to commute from residence i to workplace j as:

$$\begin{aligned} \lambda_{ij} &= \frac{\psi_{ij}}{\psi} \\ &= \frac{B_i \left(P_i^\alpha Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^\epsilon}{\sum_r^M \sum_t^M B_r \left(P_r^\alpha Q_r^{1-\alpha} k_{ij}\right)^{-\epsilon} w_t^\epsilon}. \end{aligned} \tag{A.11}$$

In addition, the probability that a worker residing in i chooses area j as the workplace, $\lambda_{ij|i}^R$, is

$$
\begin{aligned}
\lambda_{ij|i}^R := \frac{\lambda_{ij}}{\lambda_i^R} &= \Pr[u_{ij} \geq \max\{u_{it}\},\ \forall t] \\
&= \int_0^\infty \prod_{t \neq j} G_{it}(u) g_{ij}(u) du \\
&= \int_0^\infty e^{-\psi_i u^{-\epsilon}} \epsilon \psi_{ij} u^{-(\epsilon+1)} du,
\end{aligned}
\tag{A.12}
$$

which we can rewrite as

$$
\begin{aligned}
\lambda_{ij|i}^R &= \frac{B_i \left(P^\alpha Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^\epsilon}{\sum_t^M B_i \left(P^\alpha Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_t^\epsilon} \\
&= \frac{(w_j/k_{ij})^\epsilon}{\sum_t^M (w_t/k_{it})^\epsilon}
\end{aligned}
\tag{A.13}
$$

Moreover, the commuter market clearing condition implies that

$$
\begin{aligned}
L_j &= \sum_i \lambda_{ij|i}^R R_i \\
&= \sum_i^M \frac{(w_j/k_{ij})^\epsilon}{\sum_t^M (w_t/k_{it})^\epsilon} R_i,
\end{aligned}
\tag{A.14}
$$

which means that the workers working in area j equal the sum of the workers who choose area j as the workplace. Finally, the expected wage of a worker residing i, $\bar{w}_i$, is

$$
\begin{aligned}
\bar{w}_i &= \mathbb{E}[w|i] \\
&= \sum_j^M \lambda_{ij|i}^R w_j \\
&= \sum_j^M \frac{(w_j/k_{ij})^\epsilon}{\sum_t^M (w_t/k_{it})^\epsilon} w_j.
\end{aligned}
\tag{A.15}
$$

A.2 Existence and Uniqueness

Given the parameters in our model $\{\alpha, \beta, \mu, \epsilon, d\}$, the reservation utility level in the wider economy $\bar{U}$, and exogenous location characteristics vector $\{\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{k}\}$, the general equilibrium of this model is referenced by the vector $\{\boldsymbol{L}, \boldsymbol{R}, \boldsymbol{Q}, \boldsymbol{w}, \bar{\boldsymbol{w}}, \bar{L}\}$. Given this equilibrium vector and scalar, the other endogenous variables can be determined. The following sets of equations determine the equilibrium vector: workplace choice probabilities (11), residential choice probabilities (12), expected wage in residential city i (14), zero profit conditions (18), land market clearing conditions

(19), and population mobility (15).[32]

Workplace choice probabilities

$$\lambda_j^L = \frac{\sum_i^M B_i \left(P_i^\alpha Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^\epsilon}{\sum_r^M \sum_t^M B_r \left(P_r^\alpha Q_r^{1-\alpha} k_{rt}\right)^{-\epsilon} w_t^\epsilon} \tag{A.16}$$

Residential choice probabilities

$$\lambda_i^R = \frac{\sum_j^M B_i \left(P_i^\alpha Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} w_j^\epsilon}{\sum_r^M \sum_t^M B_r \left(P_r^\alpha Q_r^{1-\alpha} k_{ij}\right)^{-\epsilon} w_t^\epsilon}. \tag{A.17}$$

Expected wage in residential city

$$\bar{w}_i = \sum_j^M \frac{(w_j/k_{ij})^\epsilon}{\sum_t^M (w_t/k_{it})^\epsilon} w_j \tag{A.18}$$

Zero profit condition

$$w_j = \beta A_j^\beta \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta} \tag{A.19}$$

Land market clearing condition

$$H_i = (1-\alpha)\frac{\bar{w}_i}{Q_i} R_i + \left(\frac{(1-\beta)A_i}{Q_i}\right)^{1/\beta} L_i \tag{A.20}$$

Population mobility

$$\eta \left[\sum_r^M \sum_t^M B_r (P_r^\alpha Q_r^{1-\alpha} k_{rt})^{-\epsilon} w_t^\epsilon\right]^{1/\epsilon} = \bar{U} \tag{A.21}$$

From population mobility and zero profit condition, residential choice probability can be rewritten as:

$$\begin{aligned} \lambda_i^R &= \frac{R_i}{\bar{L}} \\ &= \left(\frac{\bar{U}}{\eta}\right)^{-\epsilon} \sum_j^M B_i \left(Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} \left(\beta A_j^\beta \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta}\right)^\epsilon. \end{aligned} \tag{A.22}$$

[32] This subsection follows Ahlfeldt et al. (2015).

Workplace choice probability is also:

$$\begin{aligned}
\lambda_i^L &= \frac{L_i}{\bar{L}} \\
&= \left(\frac{\bar{U}}{\eta}\right)^{-\epsilon} \sum_i^M B_i \left(Q_i^{1-\alpha} k_{ij}\right)^{\epsilon} \left(\beta A_j^{\beta} \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta}\right)^{\epsilon}.
\end{aligned} \tag{A.23}$$

Substituting zero profit condition into expected wage in residential city i:

$$\bar{w_i} = \sum_j^M \frac{\left(\beta A_j^{\beta} \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta} / k_{ij}\right)^{\epsilon}}{\sum_t^M \left(\beta A_t^{\beta} \left(\frac{1-\beta}{Q_t}\right)^{(1-\beta)/\beta} / k_{it}\right)^{\epsilon}} \left(\beta A_j^{\beta} \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta}\right). \tag{A.24}$$

Substituting (A.22), (A.23), and (A.24) into land market clearing condition:

$$\begin{aligned}
D_i(\boldsymbol{Q}) =&(1-\alpha) \sum_j^M \frac{\left(\beta A_j^{\beta} \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta} / k_{ij}\right)^{\epsilon}}{\sum_t^M \left(\beta A_t^{\beta} \left(\frac{1-\beta}{Q_t}\right)^{(1-\beta)/\beta} / k_{it}\right)^{\epsilon}} \left(\beta A_j^{\beta} \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta}\right) \\
& \sum_j^M B_i \left(Q_i^{1-\alpha} k_{ij}\right)^{-\epsilon} \left(\beta A_j^{\beta} \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta}\right)^{\epsilon} / Q_i \\
& + \left(\frac{(1-\beta)A_i}{Q_i}\right)^{1/\beta} \sum_i^M B_i \left(Q_i^{1-\alpha} k_{ij}\right)^{\epsilon} \left(\beta A_j^{\beta} \left(\frac{1-\beta}{Q_j}\right)^{(1-\beta)/\beta}\right)^{\epsilon} \\
=& H_i
\end{aligned} \tag{A.25}$$

where we assume the measure utility; in other words, $(\bar{U}/\eta)^{\epsilon}/\bar{L} = 1$. These land market clearing condition provides a system of M equations in the M unknown floor price Q_i for each city i, and this floor price has the following properties:

$$\begin{aligned}
\lim_{Q_i \to 0} D_i(\boldsymbol{Q}) &= \infty > H_i \\
\lim_{Q_i \to \infty} D_i(\boldsymbol{Q}) &= 0 < H_i \\
\frac{dD_i(\boldsymbol{Q})}{dQ_i} &< 0 \\
\frac{dD_i(\boldsymbol{Q})}{dQ_j} &< 0 \\
\left|\frac{dD_i(\boldsymbol{Q})}{dQ_i}\right| &> \left|\frac{dD_i(\boldsymbol{Q})}{dQ_j}\right|.
\end{aligned}$$

There exists a unique vector of floor price $\boldsymbol{Q}$. Using this floor price, we obtain the equilibrium wage vector $\boldsymbol{w}$ from the zero profit condition and the vector of expected wage in residential city

$\bar{\boldsymbol{w}}$. From the vector $\{\boldsymbol{Q}, \boldsymbol{w}\}$, residence and workplace probability, $\boldsymbol{\lambda}^L, \boldsymbol{\lambda}^R$ can be solved, and we obtain the number of residents and workplace employment $\boldsymbol{L}, \boldsymbol{R}$.

A.3 Robustness Check for Numerical Calculation

We set parameters based on Ahlfeld et al. (2015), Brinkman (2016), Lucas and Rossi-Hansberg (2002), and Saiz (2010). Brinkman (2016), Lucas and Rossi-Hansberg (2002), and Saiz (2010) use U.S. data, however, parameter of spatial decay, $\rho_{.}$ is based on Ahlfeldt et al. (2015) ,which uses data on Germany. Hence, we change these parameters $\rho_{.}$ to $0.8\rho_{.}$ and $1.2\rho_{.}$. Table 7 shows the results for robustness check of numerical calculation. The result is very similar to the main result in Table 1. In addition, our hypothesis on empirical analysis, that is, the relationship between the number of highway rays and the reduction of population is convex and monotone decreasing when workers do not take congestion into account, and that relationship is only monotone decreasing when workers take congestion into account, is also the same in robustness check. Table 8 shows the effect of additional highway rays on central city populations, calculated by $\Delta \log \mathrm{CCpop} - \Delta \log \bar{L}$.

B Details on Chernozhukov et. al. (2013)

Chernozhukov, Lee, and Rosen (2013) proposed the a median-bias-corrected estimation methodology of partial identification to take a finite sample bias into account. We use this method to estimate the bounds on $E[p(t)]$ in (30), and (34), and on $E[p(t_2)] - E[p(t_1)]$ in (31), and (35). In this section, we describe the steps for implementation of Chernozhukov et. al. (2013). We describe the lower bound of (30) for instance.

Step 1. Set $\gamma_n \equiv 1 - 0.1/\log n$. Simulate $R \times n$ independent draws from $N(0,1)$, denoted by $\{\varpi_{ir} : i = 1, \cdots, n, r = 1, \cdots, R\}$, where n is the sample size and R is the number of simulation repetitions ($R = 10,000$).

Step 2. Compute the local kernel estimator $\hat{E}[y_i|z_i]$ using the quadratic kernel and the rule-of-thumb bandwidth, and define $\hat{U}_i$ as the kernel type regression residual.

Table 7: Results of numerical calculations

	Number of highway rays						
	0	1	2	3	4	5	6
$m = 0,\ 0.8\rho_a$							
L_c	0.588	0.605	0.616	0.624	0.630	0.635	0.639
R_c	0.400	0.368	0.349	0.336	0.327	0.321	0.318
$\bar{L}$	0.092	0.120	0.149	0.180	0.212	0.245	0.279
$m = 0,\ 1.2\rho_a$							
L_c	0.673	0.690	0.701	0.709	0.715	0.720	0.724
R_c	0.447	0.399	0.368	0.348	0.334	0.324	0.317
$\bar{L}$	0.075	0.098	0.122	0.147	0.173	0.200	0.228
$m = 0.5,\ 0.8\rho_a$							
L_c	0.588	0.576	0.563	0.551	0.540	0.530	0.522
R_c	0.400	0.390	0.380	0.369	0.356	0.343	0.328
$\bar{L}$	0.092	0.106	0.119	0.131	0.142	0.154	0.165
$m = 0.5,\ 1.2\rho_a$							
L_c	0.673	0.662	0.650	0.639	0.629	0.620	0.612
R_c	0.447	0.428	0.412	0.396	0.380	0.363	0.345
$\bar{L}$	0.075	0.087	0.098	0.108	0.118	0.127	0.136
$m = 0,\ 0.8\rho_b$							
L_c	0.632	0.649	0.660	0.668	0.674	0.679	0.683
R_c	0.425	0.385	0.360	0.343	0.332	0.324	0.319
$\bar{L}$	0.083	0.108	0.135	0.163	0.191	0.221	0.252
$m = 0,\ 1.2\rho_b$							
L_c	0.632	0.648	0.660	0.668	0.674	0.679	0.683
R_c	0.424	0.383	0.358	0.341	0.330	0.322	0.316
$\bar{L}$	0.083	0.108	0.134	0.162	0.190	0.220	0.251
$m = 0.5,\ 0.8\rho_b$							
L_c	0.632	0.620	0.608	0.596	0.585	0.575	0.567
R_c	0.424	0.410	0.397	0.384	0.370	0.355	0.338
$\bar{L}$	0.083	0.096	0.107	0.119	0.129	0.140	0.150
$m = 0.5,\ 1.2\rho_b$							
L_c	0.632	0.620	0.607	0.596	0.585	0.575	0.567
R_c	0.424	0.409	0.396	0.383	0.368	0.353	0.336
$\bar{L}$	0.083	0.095	0.107	0.118	0.129	0.139	0.150

Note. λ_c^L and λ_c^R indicate the proportion of employment and residents in the central city, respectively. $\bar{L}$ shows the total employment in the metropolitan area.

Table 8: The effect of change in the number of highways

	Change in the number of highways					
	0 - 1	1 - 2	2 - 3	3 - 4	4 - 5	5 - 6
$m = 0,\ 0.8\rho_a$	-0.036	-0.024	-0.016	-0.011	-0.008	-0.005
$m = 0,\ 1.2\rho_a$	-0.050	-0.034	-0.025	-0.018	-0.013	-0.009
$m = 0.5,\ 0.8\rho_a$	-0.012	-0.012	-0.013	-0.015	-0.017	-0.020
$m = 0.5,\ 1.2\rho_a$	-0.019	-0.017	-0.017	-0.018	-0.020	-0.022
$m = 0,\ 0.8\rho_b$	-0.043	-0.029	-0.020	-0.014	-0.010	-0.007
$m = 0,\ 1.2\rho_b$	-0.044	-0.030	-0.021	-0.015	-0.011	-0.008
$m = 0.5,\ 0.8\rho_b$	-0.015	-0.014	-0.015	-0.016	-0.018	-0.021
$m = 0.5,\ 1.2\rho_b$	-0.015	-0.014	-0.015	-0.016	-0.018	-0.021

Note. Each entry shows the results of $\Delta \log \mathrm{CCpop} - \Delta \log \bar{L}$. These entries show the effect of change in the number of highways on central city populations considering the change in total employment.

Step 3. For each $u \in V$ and $r = 1, \cdots, R$, compute the estimators

$$\begin{aligned} \hat{MU}_n(u) &= \sum_{t \le s} \hat{E}[p|z = s, v = u] \Pr(z = s|v = u) + p_0 \Pr(z < t|v = u) \\ \hat{g}_u^{MU} &= \sum_{t \le s} \hat{U}_i \frac{K\left(\frac{s - Z_i}{h_n}\right)}{\sqrt{h_n} \hat{f}_n(s)} \Pr(z = s|v = u) + p_0 \Pr(z < t|v = u) \\ G_n(\hat{g}_u^{MU}) &= \frac{1}{\sqrt{n}} \sum_{i=1}^{n} \varpi_{ir} \hat{g}_u^{MU}, \end{aligned}$$

where $\hat{f}_n(s)$ is the kernel density estimator of the density of ϖ and h_n is a bandwidth. Let $s_n^2(u)^{MU} = E_n[(\hat{g}_u^{MU})^2]/(nh_n)$ and $E_n[(\hat{g}_u^{MU})^2] = n^{-1} \sum_{i=1}^{n} (\hat{g}_u^{MU})^2$.

Step 4. Compute $k_{n,V}(\gamma_n) = \gamma_n$- quantile of $\{\max_{u \in V} G_n(\hat{g}_u^{MU})/\sqrt{E_n[(\hat{g}_v^{MU})^2]}, r = 1, \cdots, R\}$, and $\hat{V}_n = \{u \in V : \hat{MU}_n(u) \le \max_{u \in V} (\hat{MU}_n(u) + k_{n,V}(\gamma_n) s_n(u)) + 2k_{n,V}(\gamma_n) s_n(u)\}$.

Step 5. Compute $k_{n,\hat{V}}(p)$ = p-quantile of $\{\max_{u \in \hat{V}} G_n(\hat{g}_u^{MU})/\sqrt{E_n[(\hat{g}_v^{MU})^2]}, r = 1, \cdots, R\}$, and set $\hat{MU}_n(p) = \max_{u \in V} [\hat{MU}_n(u) + k_{n,\hat{V}}(p) s_n(u)]$. $\hat{MU}_n(p)$ is the bias-corrected estimates or the end points of confidence intervals, depending on p, for instance, $p = 0.5$ or $p = 1 - \alpha$.

C Details of estimation results

C.1 The background of (36)

The relationship between highway rays and the central city population can be written as

$$\log(\mathrm{CCpop}_y) = b_0 + b_1 z_y + \boldsymbol{b}\boldsymbol{x}_y + \vartheta + \varepsilon_y,$$

where y is year, $\boldsymbol{x}$ denotes a vector of observed variables, ϑ denotes the unobserved constant central city specific variable, and ε_y is the time-varying error term. However, Duranton and Turner (2012) find that highways cause the metropolitan population to increase, and this effect includes central cities also. Hence, b_0 captures the direct and indirect effect of highway rays. The direct effect indicates that a new highway ray reduces the central city population, and the indirect effect implies that a new highway ray increases the central city population because it attracts a new population from outside the metropolitan area. We take metropolitan population into account, and the estimation equation is rewritten as

$$\log(\text{CCpop}_y) - \log(\text{MSApop}_y) = b'_0 + b'_1 z_y + \boldsymbol{b'}\boldsymbol{x}_y + \vartheta + \varepsilon_y. \tag{C.26}$$

Our estimation equation is written as

$$\log(\text{CCpop}_y) = b_0 + b_1 z_y + b_2 \log(\text{MSApop}_y) + \boldsymbol{b}\boldsymbol{x}_y + \vartheta + \varepsilon_y. \tag{C.27}$$

According to Baum-Snow et al. (2017), (C.26) is decomposed into

$$\begin{aligned}\log(\text{CCpop}_y) &= b_0 + b_1 z_y + \boldsymbol{b}\boldsymbol{x}_y + \vartheta + \varepsilon_y,\\ \log(\text{MSApop}_y) &= b'_{a0} + b'_{a1} z_y + \boldsymbol{b}'_a\boldsymbol{x}_y + \vartheta_a + \varepsilon_{ay}.\end{aligned}$$

These equations show that log(MSApop) affects log(CCpop), and these variables are affected by the number of rays. Hence, there is potential endogeneity in this estimation. Our estimation strategy accounts for this endogeneity in section 4.3.1.

We use first difference to examine the causal effect of highway rays on the central city population. The equation for 1950 is

$$\log(\text{CCpop}_{1950}) = b_0^{1950} + b_1^{1950} z_{1950} + b_2^{1950} \log(\text{MSApop}_{1950}) + \boldsymbol{b}^{1950}\boldsymbol{x}_{1950} + \vartheta + \varepsilon_{1950}.$$

First difference is

$$\Delta \log(\text{CCpop}) = \beta_0 + \beta_1 \Delta z_t + \beta_2 \Delta \log(\text{MSApop}) + \boldsymbol{\beta}\boldsymbol{x} + \Delta\varepsilon.$$

This is our primary estimation equation.

C.2 The results of first stage point estimation

Table 9 shows the results of the first stage point estimation. We estimate (36) with the instrumental variable of the 1947 plan. Specifically, the first stage of this estimation is the following equation:

$$z_j = \gamma_1 \ v_j + \boldsymbol{\gamma X} + \epsilon$$

All of the results imply that the instrumental variables are a good variation for the real construction of new highways.

Table 9: First stage point estimation

	1.	2.	3.	4.	5.
(i)	0.476***	0.531***	0.543***	0.509***	0.528***
	(9.56)	(8.49)	(6.85)	(8.11)	(8.48)
F-value	91.40	72.04	46.85	65.76	71.87
(ii)	0.472***	0.527***	0.540***	0.511***	0.524***
	(9.64)	(8.26)	(6.94)	(8.30)	(8.23)
F-value	93.02	68.15	48.12	68.87	67.71
(iii)	0.441***	0.512***	0.532***	0.480***	0.514***
	(8.93)	(8.00)	(7.30)	(7.54)	(7.98)
F-value	79.67	63.94	53.34	56.85	63.67
(iv)	0.445***	0.517***	0.546***	0.494***	0.519***
	(9.31)	(7.85)	(7.53)	(8.06)	(8.01)
F-value	86.65	61.65	56.65	64.92	64.22
(v)	0.336***	0.40***	0.442**	0.388***	0.422***
	(7.01)	(6.63)	(6.24)	(6.77)	(7.12)
F-value	49.15	43.91	38.95	45.81	50.70
No. Obs.	240	151	111	165	139

We use five data sets: 1. Data on MSAs in 2000, 2. Data on cities whose central city populations were at least 50,000 in 1950. 3. Data on cities with central city populations larger than 75,000 in 1950. 4. Data on cities with an MSA population larger than 100,000 in 1950. 5. Data on cities with a central city population larger than 50,000 and an MSA population larger than 100,000 in 1950.
The entries indicate the coefficients of the 1947 planned rays, and the standard errors are clustered by the state of the MSA. With this standard error, we provide the t-values in parentheses and ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. F-value indicates the first stage of the result of first stage regressions.

In addition, we use the 1497 plan and national population growth from 1950 to 1990 excluding the metropolitan area populations as an instrumental variable in section 4.2.2. Table 10 shows the results of first stage point estimation with data on cities whose central city populations were at least 50,000 in 1950.

Table 10: The results of first stage estimation: populated central cities in 1950

	C.C. rays in 1990 (D)					Δlog(MSA pop.)		
	(viii)	(ix)	(x)	(xi)	(xii)	(viii)	(ix)	(x)
Instrument								
1947*plan*	0.528***	0.545***	0.399***	0.514***	0.524***	0.019	0.037**	-0.002
	(8.93)	(9.04)	(7.03)	(8.02)	(8.97)	(1.33)	(2.29)	(-0.14)
National Pop. Growth	-156.3***	-130.8**	-213.6***	0.777***	-246.6**	-183.3***	-155.9***	-192.8***
	(-3.15)	(-1.98)	(-3.76)	(3.74)	(-2.52)	(-3.19)	(-3.42)	(-3.36)
Controls								
C.C. radius in 1950	0.290***	0.262***	0.125	0.266***	0.229	0.050	0.020	0.022
	(3.47)	(2.68)	(1.30)	(2.79)	(2.04)	(1.41)	(0.59)	(0.51)
Δ log(simulated income)	0.234	-26.4	1.782	-1.22	0.131	1.859***	-26.7***	2.117***
	(0.10)	(-1.19)	(0.83)	(0.62)	(0.06)	(3.76)	(-4.28)	(4.83)
ΔGini coeff.		-97.9					-104.8***	
		(-1.17)					(-4.50)	
log(MSA pop. in 1950)			0.559***					0.093*
			(5.12)					(1.77)
log(MSA pop. in 1940)				-0.039	0.154			
				(-0.48)	(1.22)			
Obs.	151	151	151	151	151	151	151	151
First stage F-stat.	37.6	21.2	24.2	64.3	43.91	37.6	21.2	24.2
S-W F-stat.	75.0	71.9	47.9	64.3	43.91	27.1	16.1	38.3

Note. We use the data for central city with a population of at least 50,000. We provide the t-values in parentheses with standard errors clustered by the state of the MSA. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. In this estimation, we use the number of rays in the 1947 plan and national population growth from 1950 to 1990 excluding the metropolitan area population as the instrumental variables, and every regression includes a constant. First stage F-statistics is Kleibergen-Paap F statistics, and S-W F-statistics is statistics for Sanderson-Windmeijer multivariate F test.

C.3 The results of point estimation

In addition, Table 11 presents the estimates of equation (36), specifically, data on cities whose central city population were at least 50,000 in 1950.

Table 11: The results of estimation: populated central city in 1950

	(i)	(ii)	(iii)	(iv)	(v)
C.C. rays in 1990	-0.108***	-0.113***	-0.130***	-0.120***	-0.099*
	(-3.34)	(-3.39)	(-4.03)	(-4.08)	(-1.92)
C.C. radius in 1950	0.105***	0.121***	0.443***	0.388***	0.420***
	(4.80)	(4.80)	(4.87)	(5.26)	(4.04)
Δ log(simulated income)		1.293**	0.107***	0.099***	0.120***
		(2.43)	(5.06)	(4.78)	(6.44)
Δ log(MSA pop.)		0.100	-7.042	-0.099	
		(0.24)	(-1.29)	(-0.22)	
ΔGini coeff.				-26.569	
				(-1.29)	
log(MSA pop. in 1950)					-0.071
					(-1.25)
Obs.	151	151	151	151	151
First stage stat.	72.04	68.15	63.94	61.65	43.91

We use the data for central city's populations with at least 50,000. We provide the t-values in parentheses with standard errors clustered by the state of the MSA. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All of the estimations use the number of rays in the 1947 plan as the instrumental variable.

D Descriptive statistics

See Table 12.

Table 12: Descriptive Statistics

variable	mean	sd	min	max
Δ log(CC pop.)	-0.209	0.335	-0.961	1.318
z (realized treatment)	2.871	1.588	1	6
v (instrumental variable)	2.900	1.527	1	6
CC area in 1950 (mile^2)	27.388	44.133	3.7	450.9
MSA area in 1950 (mile^2)	2061.783	2276.639	199	27270
log(MSA pop.)	0.602	0.436	-0.209	2.705
Δ log(MSA pop.)	-1.613	1.038	-3.380	2.587
Δ simulated income	0.604	0.170	0.2028	1.033
ΔGini coefficient	0.033	0.023	-0.038	0.069

In these descriptive statistics, we use data for all cities of metropolitan areas in 1990. We used p, z, and v for point and bound estimations.

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