Evaluating Transportation Improvements Within Cities Using Quantitative Spatial Models

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Abstract

Quantitative spatial models (QSMs) offer an economically and geographically realistic framework to evaluate the effects of transportation infrastructure within cities. In this survey, I argue that QSMs are most compelling when complemented by credible research design. To do so, I review alternative economic valuation methods and develop a simple urban QSM to interpret changes accessibility. The model maps the estimands of the alternative approaches into a consistent framework, demonstrating that standard empirical research designs can be conformable with QSM estimation. This exercise reveals several shortcomings common in applications of QSMs. These shortcomings, along with model enrichments, inform the future agenda of this literature.

Keywords: quantitative spatial models, transportation infrastructure, transit, urban economics

JEL Codes: R40, R41, O18

"Beware of certainty where none exists."

—*Daniel Patrick Moynihan*

1 Introduction

Quantitative spatial models (QSMs) have become a common economic paradigm for evaluating urban transportation improvements, despite the relative youth of the modeling framework. QSMs enable researchers to incorporate several margins of adjustment in response to transportation innovations as well as downstream general equilibrium effects. These models represent spatial heterogeneity in a somewhat realistic way and so deliver counterfactuals with rich variation in spatial

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responses. Moreover, QSMs naturally embed a concept of welfare, making it straightforward to calculate the benefits of transit and roadways and assess efficacy relative to costs.

Despite the clear benefits of this paradigm, there is little guidance on how to best use these models to evaluate the effects of changes in urban transportation or to validate their output. Current research varies widely as to what economic features are modeled, how effects are measured, and which identification and calibration strategies are robust. Certainly, the sharpness of the predictions from any particular model is a strength of this literature. However, this sharpness can also create the impression of certainty in quantifying the effects of urban transportation projects when, in fact, conclusions are much less certain.[1]

In this survey, I address this gap with five contributions. First, I summarize various economic approaches for measuring the effects of transportation improvements and motivations for using QSMs. Second, I use a simple urban QSM to map the estimands of hedonic, sorting, travel-demand, and gravity methods into a common framework, demonstrating how these methods can inform parameter identification. Third, I discuss research designs in the context of QSMs and show how interference (i.e., general equilibrium effects) can alter the interpretation of reduced-form estimates without precluding consistent estimation of model parameters. Then, I review the literature using QSMs to evaluate urban transportation improvements and synthesize its findings. Lastly, I explore useful model enrichments and develop an agenda for credible QSM use for transportation infrastructure valuation.

A clear argument emerges: QSMs are not a substitute for research design and are at their most compelling when accompanied by careful, well-identified arguments. Evaluating urban transportation infrastructure via QSMs is most credible when (i) there is a well-identified causal link from infrastructure to travel costs, flows, or other fundamentals, (ii) the mapping from fundamentals to equilibrium outcomes is clear and appropriate (local) to the research setting, and (iii) the uncertainty induced by parameter selection and model specification is explicit. Care must be taken when borrowing parameters across contexts and questions; QSMs ignore parameter identification at the peril of losing coherence with the research environment.

The survey proceeds as follows. Section 2 reviews the three primary alternative economic approaches to measuring the effects of transportation infrastructure: hedonic valuation, sorting models, and travel demand. Section 3 then lists the motivations for adopting QSMs. Though measuring welfare and accounting for equilibrium effects predominate, other reasons, such as generating latent data or enabling mechanism analysis, are also viable. I describe a simple urban QSM in Section 4 and build intuition for how the model maps outcomes to fundamentals. Section 5 demonstrates how the QSM measures the effects of transportation infrastructure. To demonstrate that QSM estimation can be informed by quasi-experimental research designs, this section derives linear estimating equations that embed alternative approaches for valuing transportation infras-

1. The epigraph for this article is taken from Donald Shoup's "Truth in Transportation Planning" (Shoup 2003).

tructure yet are consistent with the QSM. I also clarify that a motivation for using QSMs—that the Stable Unit Treatment Value Assumption (SUTVA) is violated and so model-free unbiased treatment effects cannot be recovered—affects the interpretation of estimands rather than the consistency of parameter estimates. Section 6 surveys the extant literature and highlights emergent themes.[2] Finally, Section 7 broadly discusses growth areas and shortcomings of urban QSM implementations. Continued incorporation of heterogeneity and dynamics into QSMs will enrich the space of questions available for study. However, because QSMs often match observed data perfectly, even unreasonable models can explain the observed spatial distribution of economic activity. Thus, I conclude by reviewing the shortcomings of QSMs to advocate for credible application, validation, and quantification of uncertainty in these models.

QSMs are a powerful and useful tool, and like any tool, it matters *how* they are used. My hope is to increase the transparency of both the benefits and shortcomings of QSMs for the study of urban transportation and to bridge the policy evaluation literature of applied microeconomics with the applied theory approach of QSMs. In that sense, this review complements other recent reviews that contemplate infrastructure evaluation with QSMs.[3]

2 QSM Antecedents

There are several ways to measure the value of urban transportation projects. Economists have typically focused on three methods: hedonic valuation, equilibrium sorting models, and travel demand analysis. Collectively, these methods enable researchers to model a wide variety of urban phenomena in response to transportation interventions. QSMs complement, combine, and often extend these approaches. Section 5 integrates these methods into QSMs, revealing them to be informative about the margins QSMs consider.

Hedonics

Hedonic analysis of transportation measures the effects of exposure or proximity to the transportation system on property values. Its intellectual tradition is based on the capitalization of amenities, such as those provided by transportation access, into property values in equilibrium. Ceteris paribus, properties with better transportation access will be priced higher than others. This

2. This review generally considers 'urban' QSMs. A reasonable conceptual distinction between urban and other QSMs is the spatial separation of housing from production. Because I focus on QSMs, I do not extensively consider related papers focused on optimal urban transportation policy that do not embed general equilibrium. For this, see Almagro and Kreindler (2026) in this volume.

3. Particularly useful is Redding and Turner (2015), who combine a QSM framework with discussion of causal identification. Redding (2025) applies Ahlfeldt et al. (2015) to study hypothetical transportation improvements and contrasts a market-access only approach with a full QSM. And although Donaldson (2025) centers on a sufficient statistics framework, it contains enlightening sections on measurement and causal identification.

difference in price can be used to understand households' willingness to pay for transportation access.[4]

While conceptually straightforward, early applications of this approach often suffered from measurement and endogeneity challenges, as it is difficult to separate the benefits of transportation access from the many other residential amenities households value. More recent literature uses quasi-experimental variation in transportation exposure to estimate causal effects of transportation on property values (e.g., Baum-Snow and Kahn 2000; Billings 2011; Gupta, Van Nieuwerburgh, and Kontokosta 2022). Although these approaches provide causal estimates of capitalization or price effects, additional assumptions are still required to recover willingness to pay or welfare because changes in amenities can alter the equilibrium price schedule and induce sorting (Banzhaf 2021).

Sorting Models

Sorting models instead seek to capture revealed valuation of transportation amenities through the lens of discrete residential neighborhood choice. Like hedonic analysis, these models note that location choice embeds transportation access. However, by discretizing the choice space, equilibrium sorting models can explicitly model a wide degree of heterogeneity in preferences.[5] Barwick et al. (2024), Chernoff and Craig (2022), and Mulalic and Rouwendal (2020) are examples of using equilibrium sorting models to value transportation access and show how these models can reflect heterogeneity in valuing many residential characteristics, beyond transportation access. Like hedonic models, equilibrium sorting models can struggle to separate the benefits of transportation access from other residential amenities, though modern sorting models do sometimes include workplace. But because workplace is treated as fixed, these models cannot quantify how transportation shifts the equilibrium spatial distribution of production and consumption.

Travel Demand Analysis

Although it often shares discrete choice methods with the sorting paradigm, travel demand analysis has an independent history. Fogel (1964) introduces a social savings approach that calculates the value of travel time saved from infrastructure, and McFadden (1974) embeds this into a random utility discrete choice model. In this literature, the focus is typically on understanding agents' mode choice problem, along with some attention to trip generation and routing.[6] Given this, the travel demand literature typically recovers estimates reflecting the marginal disutility of travel time or the marginal value of time, and recovers estimates of the value of travel time savings (VTTS) from transportation projects (Moses and Williamson 1963). It is less well-equipped to

4. The capitalization of transportation into housing prices has been studied since at least Spengler (1930).
5. See Wong (2018) for an integration of hedonic and discrete choice approaches that aims at comparability.
6. For a detailed treatment, see Small and Verhoef (2007).

model larger scale responses to transit, such as sorting and development, and is not equipped to model changes in economic geography. That said, the richness of this approach means that it is often nested within equilibrium sorting models and within QSMs (e.g., Tsivanidis 2026).

3 Why Use QSMs?

The use of QSMs is typically motivated by or advocated for using one (or more) of the following arguments.

Equilibrium Effects Are Important

In an urban economy, residential and production location choices are determined in spatial equilibrium, which interconnects all places within a city. Through such a lens, there is no distinction between locations affected by changes in transportation and unaffected locations. Thus, there are no clean control locations, a violation of SUTVA (Angrist, Imbens, and Rubin 1996). When SUTVA is violated, average treatment effects cannot be consistently estimated using standard quasi-experimental techniques (Alves, Burton, and Fleitas 2025) (though see Section 5.6 to see how such techniques are still useful). Agglomeration forces can also substantively alter the economic geography of cities (e.g., Ahlfeldt et al. 2015). Small or localized transportation projects may have only an epsilon effect in other parts of the city, and so may ignore this concern. But large, substantial changes to infrastructure have spillovers that may spread throughout a city.

Welfare

As long as a QSM provides a reasonable approximation of the relevant economic environment, it naturally generates a measure of how welfare responds to small and moderately sized changes in transportation infrastructure (e.g., Donaldson 2025). Although the notion of welfare embedded in simple QSMs may be somewhat unsatisfactory (as it takes the frame of a new resident with no local attachment or knowledge moving into the city), more nuanced models can incorporate heterogeneous groups, incumbency, or local attachment (e.g., Chang 2025; Tsivanidis 2026). Given the often substantial costs of transportation infrastructure, measuring welfare can be particularly useful for benefit-cost comparisons and project evaluation.

Mechanism Analysis and Decomposition

QSMs can incorporate and reflect a variety of mechanisms by which transportation infrastructure shifts urban outcomes. For example, model counterfactuals can toggle housing supply or labor demand responses to isolate partial and general equilibrium effects. Or, models can vary the intensity and spatial kernel of spillovers to understand the role that spillovers play. For example, QSMs can separately account for the access versus amenity tradeoffs that may come with some transportation infrastructure (Brinkman and Lin 2024; Bagagli 2025; Weiwu 2025). The use of QSMs for policy evaluation also allows the potential for assessing the complementarity or substitutability of different channels.

Network Effects

By modeling travel between all places within a city, QSMs are well equipped to capture the network effects of transportation infrastructure. They can capture complementarities between routes, modes, and places, particularly if the model incorporates multimodal routes, consumption travel, and/or trip chaining (Allen and Arkolakis 2022; Miyauchi, Nakajima, and Redding 2025). Although travel demand analysis can reflect network effects, those studies do not always build a sufficiently broad sample of trips to convincingly aggregate travel decisions within cities.

Market Access as Measurement

QSMs generate market access terms that summarize the proximity of residents to desirable employment locations and of firms to pools of workers. These market access terms are interesting in and of themselves for measurement, in the tradition of Harris (1954). For example, Baum-Snow, Hartley, and Lee (2019) use market access terms to measure the desirability of neighborhoods by education status, Harari (2024) and bunten et al. (2024) use market access to study segregation.

Structural Approach to Identification

QSMs provide a scaffolding to develop instruments that provide an omnibus approach to identification. For example, Baum-Snow and Han (2024) use tract-level shift-share labor demand instruments to estimate heterogeneous housing supply elasticities and Severen (2023) shows how such instruments can generally identify local housing and labor supply and demand elasticities. Even when not used to develop instrumental variables, the framework of QSMs may be helpful to parse potential sources of endogeneity, as shown in Section 5.5.

For Data Generation and Measuring Unobservables

Finally, QSMs can also be viewed as part of a data generating process, allowing researchers to fill in missing or unobservable data based on model predictions (Barjamovic et al. 2019; Heblich, Redding, and Sturm 2020). This is particularly useful in historical settings where data resources may be sparse. In addition to historical settings, cities in developing settings may also have sparser data resources that QSMs can help overcome (Sturm, Takeda, and Venables 2023). A not uncommon QSM use is to assert market clearing conditions that allow recovering prices (wages and rents), though this is only possible under restrictive assumptions (e.g., Takeda and Yamagishi 2024).

4 A Simple Urban Quantitative Spatial Model

The QSM described in this section is used to study the effects of urban transportation in Severen (2023). It shares many features with—and is readily extensible to—Ahlfeldt et al. (2015), but is somewhat simpler in that it assumes exogenous land use and no agglomeration or endogenized amenities. It also features homothetic agents homogeneous except for idiosyncratic location-pair preferences and absentee landlords, and it is a closed city. As such, it focuses on the core of how labor and housing markets respond to transportation infrastructure. I write the model to accommodate a generic notion of accessibility between locations; this can nest sub-models incorporating mode or route choice (see Section 5.1).[7]

4.1 Households

Households provide one unit of labor and choose residential location and workplace to maximize utility subject to income, housing prices, and commuting costs. The choice of utility function only matters insofar as it affects indirect utility. The indirect utility of household o residing in residential location i and working j is:

$$v_{ijo} = \frac{W_j \delta_{ij}}{Q_i^{1-\zeta}} \nu_{ijo},$$

where W_j is the income earned at location j, Q_i is the per unit price of housing at i, $1 - \zeta$ is the housing expenditure share, and ν_{ijo} is household o's idiosyncratic preference for location pair ij.[8] The term δ_{ij} is an index that captures accessibility between i and j. Written as such, this *accessibility index* nests several implementations that may themselves feature interesting economic problems, aid identification, or both.[9]

The key tractability assumption in QSMs is typically that the ν_{ijo} terms are drawn from independent Fréchet distributions with a common shape parameter, ϵ, and location-specific scale parameters, Λ_{ij}. This distributional assumption (like other extreme value distributions) delivers analytically tractable probability shares that can be directly connected with data, delivering the "quantitative" in quantitative spatial modeling.

The shape parameter has several economic interpretations. The first is that ϵ governs how differently households value otherwise identical locations: for high ϵ, all households value similar

7. In constructing a model, researchers face many choices. Rather than detail those, I refer the interested reader to Redding and Rossi-Hansberg (2017) and Allen and Arkolakis (2025). Because it omits land use change, the model developed here is best suited to studying the short- to medium-run effects of urban transportation innovations in large cities with binding land use regulations.

8. Here, indirect utility is homogeneous of degree one in wage and households only provide one unit of labor, so I use wage and income interchangeably.

9. It is common to write travel costs as δ_{ij}^{-1}; I differ to maintain consistency with the several interpretations of travel costs in Section 5.

locations similarly, while for low ϵ, households may value similar locations quite differently. It also serves as the (extensive-margin) elasticity of labor supply. Finally, it also plays the role of the marginal utility of income. As a result, the value of ϵ effectively determines the magnitude of the mapping from changes in prices and accessibility to welfare.

The location-specific scale terms can be parameterized in several (often isomorphic) manners. The following parameterization highlights identification: Let $\Lambda_{ij} \equiv B_i E_j D_{ij}$, such that the cdf of ν_{ijo} is $F_{ij}(\nu) = \exp(B_i E_j D_{ij} \nu^{-\epsilon})$. In this parameterization, B_i may represent a residential amenity, E_j a workplace amenity (a labor supply shifter), and D_{ij} the average residual utility of each residential and workplace pair.[10] Although Λ_{ij} and its components are typically given names that evoke a certain interpretation (i.e., amenity), they function as (model) residuals. Literal interpretation of these variable labels warrants caution (see Ang, Angel, and Parkhomenko 2024).

The Fréchet distributional assumption is useful because it generates analytic expressions for the share of households that choose each location pair ij:

$$\pi_{ij} \equiv \frac{N_{ij}}{\bar{N}} = \frac{W_j^{\epsilon} Q_i^{-\epsilon(1-\zeta)} \delta_{ij}^{\epsilon} \Lambda_{ij}}{\sum_r \sum_s W_s^{\epsilon} Q_r^{-\epsilon(1-\zeta)} \delta_{rs}^{\epsilon} \Lambda_{rs}}, \tag{1}$$

in which $\bar{N}$ represents the total population of the city; the number of people commuting between any pair of locations is $N_{ij} = \bar{N}\pi_{ij}$. The denominator of Equation (1) simply sums values across all possible choices, and so recalls the denominator of multinomial logit choice probabilities. In fact, similar to the log-sum term for multinomial logit, taking expectations across all location pairs generates a welfare term:

$$\bar{V} = \mathbb{E}[\max_{ij} v_{ijo}] = \gamma_\epsilon \left(\sum_r \sum_s \Lambda_{rs} \left(\frac{W_s \delta_{rs}}{Q_r^{1-\zeta}} \right)^{\epsilon} \right)^{1/\epsilon}, \tag{2}$$

where $\gamma_\epsilon = \Gamma\left(\frac{\epsilon-1}{\epsilon}\right)$ and Γ is the gamma function.[11] This measure reflects a particular notion of welfare, of someone new to the city, who does not know what their realization of the idiosyncratic terms, ν_{ijo}, will be. Welfare, $\bar{V}$, is an index reflecting the average value of all locations, given the uncertainty over idiosyncratic preference.

From the household side, all the other variables needed for the model are combinations of prices, π_{ij}, and $\bar{N}$. The total residential population of i is $N_{Ri} \equiv \bar{N} \sum_s \pi_{is}$. Housing consumption by workers in j who live in i is $(1-\zeta)W_j/Q_i$. Total housing demand in i combines these two terms

10. Note that Λ_{ij} could be written directly into the indirect utility function v_{ijo}, in which case it would appear in Equation (1) as Λ_{ij}^{ϵ}. However, when this term is a residual, rescaling has no practical effect.

11. Technically, $\epsilon > 1$ is necessary for this expectation to exist. However, Equation (1) can be equivalently derived from a multinomial logit model, in which case the restriction that $\epsilon > 1$ is moot. To see this, consider households with indirect utility $U_{ij} + e_{ijo}$, where $U_{ij} = \ln \Lambda_{ij} + \epsilon \ln W_j - \epsilon(1-\zeta) \ln Q_i + \epsilon \ln \delta_{ij}$ and e_{ijo} is distributed Type 1 extreme value. This generates choice probabilities, $\exp(U_{ij}) / \left(\sum_{r,s} \exp(U_{rs})\right)$, isomorphic to Equation (1).

to sum demand across households who work in different places: $H_i = (1-\zeta)\bar{N}\sum_s \pi_{is} W_s / Q_i$. Total labor supply to j is $N_{Fj} \equiv \bar{N}\sum_r \pi_{rj}$.

4.2 Production and Housing

Perfectly competitive, atomistic firms use labor and land to produce a globally tradable good in each location j. These atomistic representative firms produce with a constant-returns-to-scale production technology separable in productivity A_j; exogenous land used in production in j is L_{Fj} ('F' represents *F*irms). Thus, aggregating across firms gives a local production function:

$$Y_j = A_j L_{Fj}^{1-\alpha} N_{Fj}^{\alpha}.$$

Because firms are measure zero, land use decisions follow profit maximization despite a locally fixed quantity of land. Perfect competition dictates that firms pay workers their marginal product,

$$W_j = \alpha A_j \left(\frac{L_{Fj}}{N_{Fj}}\right)^{1-\alpha}. \tag{3}$$

Measure-zero developers build housing using Cobb-Douglas technology in land and materials, with productivity that varies by location. An exogenously determined quantity of residential land, L_{Ri}, is owned by absentee landlords. Perfect competition in the construction industry ensures zero profits, and land is congestible, so greater density increases prices. Under these conditions, housing supply is $H_i = (Q_i/C_i)^{1/\psi} L_{Ri}$, where C_i is the inverse of housing productivity. Rearranging yields inverse housing supply:

$$Q_i = C_i \left(\frac{H_i}{L_{Ri}}\right)^{\psi}. \tag{4}$$

4.3 Equilibrium and Inversion

Equations (1)–(4) define the model. In equilibrium, housing and labor markets clear in every location. Labor market clearing requires wages such that labor demand in Equation (3) matches labor supply, $\bar{N}\sum_r \pi_{rj}$ (with π_{rj} given in Equation 1). Housing market clearing requires that housing prices are such that housing supply in Equation (4) matches aggregate local housing demand, $H_i = (1-\zeta)\bar{N}\sum_s \pi_{is} W_s / Q_i$. This equilibrium is unique under reasonably mild parametric conditions (see Severen 2023). For convenience, the set of terms A_i, C_i, and Λ_{ij} are often called fundamentals, but are model (structural) residuals. The existence and uniqueness of the equilibrium means that any non-pathological combination of fundamentals maps to a unique matrix of populations (with elements π_{ij}) and vectors of prices (with elements W_i and Q_i).[12]

12. Incorporating agglomeration forces is straightforward, though can alter equilibrium uniqueness. A typical agglomeration specification, such as in Ahlfeldt et al. (2015) is $A_i = \mathcal{A}_i \Upsilon_i^{\mu}$, where $\mathcal{A}_i$ is termed exogenous productivity,

An underappreciated point about QSMs is that much of the difference between individual papers comes from model inversion. Inversion is the process of showing which fundamentals (residuals) can be uniquely recovered conditional on observed data and parameters. Broadly (and approximately) speaking, a vector of fundamentals can be recovered for each vector of observed data (with π_{ij}, or other bilateral matrices, often counting as two vectors). The model presented here can be inverted to deliver A_i, C_i, and $\Lambda_{ij} \equiv B_i E_j D_{ij}$ given observed data on wages, housing prices, commuting flows, and accessibility. The commuting flow matrix embeds total residential and workplace population, and the four vectors of prices and populations (wages, housing costs, and the two population vectors from the commuting matrix), along with the matrices of flows and of accessibility, deliver four vectors and one matrix of fundamentals.[13]

However, it is common to reduce the number of dimensions of fundamentals due to data constraints. For example, Ahlfeldt et al. (2015) do not observe average workplace wages at a geography conformable to their model, and so cannot separately identify residuals A_i and E_i (and so only recover three unique vectors of fundamentals). As another example, Brinkman and Lin (2024) only observe residential populations, workplace populations, and travel costs, and so can only recover two unique vectors of fundamentals. In summary, the number of data vectors limits the number of fundamentals (i.e., geographic richness) that can be recovered.

4.4 Counterfactuals and Welfare

To facilitate expressing counterfactual equilibria, QSMs often rely on exact hat algebra, so called because $\hat{X} = X'/X$ for the observed and counterfactual X and X', respectively. For relative changes in fundamentals, the relative change in welfare from an observed equilibrium to a counterfactual equilibrium can be expressed as

$$\ln \hat{V} = \frac{1}{\epsilon} \ln \left(\sum_r \sum_s \pi_{rs} \hat{W}_s^{\epsilon} \hat{Q}_r^{-\epsilon(1-\zeta)} \hat{\delta}_{rs}^{\epsilon} \hat{\Lambda}_{rs} \right). \tag{5}$$

This expression makes clear that the shape parameter governing the distribution of idiosyncratic preferences over locations equally serves as the marginal utility of income (cf. Train 2009).[14]

To simulate a counterfactual equilibrium, it is sufficient to iterate over the following system of

$Y_i = \sum_s e^{\delta_{si}} N_{Fs} / L_{Fs}$ is a spatial average workplace density, and μ is the strength of agglomeration.

13. Allen and Arkolakis (2025) note that a very simple economic geography model can be written as the linear system $\lambda \mathbf{x} = \mathbf{T}\mathbf{x}$ and $\lambda \mathbf{y} = \mathbf{T}'\mathbf{y}$, where $\mathbf{x}$ and $\mathbf{y}$ are prices and populations, λ is the scale of welfare, and $\mathbf{T}$ is a matrix of fundamentals. This makes plain the notion that QSMs 'rotate' fundamentals into prices and population and vice versa. For simple models, the rotation is linear, although that typically does not hold in more complex models.

14. An implication of the closed city assumption is that the level of welfare may change in response to transportation infrastructure. In contrast, a fully open city faces a perfectly elastic supply of population, and so changes in accessibility instead alter the size of the city without impacting welfare. An intermediate assumption is to nest a migration decision between the expected value of city residence expressed in Equation (2) and a rest-of-country option (e.g., Ospital 2026).

equations until convergence:

$$\hat{\pi}_{ij} = \frac{\hat{W}_j^{\epsilon}\hat{Q}_i^{-\epsilon(1-\zeta)}\hat{\delta}_{ij}^{\epsilon}\hat{\Lambda}_{ij}}{\sum_r\sum_s \pi_{rs}\hat{W}_s^{\epsilon}\hat{Q}_r^{-\epsilon(1-\zeta)}\hat{\delta}_{rs}^{\epsilon}\hat{\Lambda}_{rs}} \tag{6}$$

$$\hat{W}_i = \hat{A}_i\left(\frac{\sum_r \pi_{ri}\hat{\pi}_{ri}}{\sum_r \pi_{ri}}\right)^{\alpha-1} \tag{7}$$

$$\hat{Q}_i = \hat{C}_i^{1/(1+\psi)}\left(\frac{\sum_s \pi_{is}\hat{\pi}_{is}W_s\hat{W}_s}{\sum_s \pi_{is}W_s}\right)^{\psi/(1+\psi)}. \tag{8}$$

If transit only affects accessibility (for example, by reducing travel times), then $\hat{\Lambda}_{ij} = 1$, as do $\hat{A}_i$ and $\hat{C}_i$. Then, the matrix $\hat{\delta}_{ij}$ can be inserted into Equation (6) and the system iterated through. Note that ϵ and the denominator of Equation (6) together can then be used to calculate welfare, as in Equation (5).

5 Measuring the Consequences of Urban Transportation

I next discuss using the model to quantify the effects of urban transportation. I focus first on measurement in the gravity (commuting) portion of the model, before shifting transportation's possible effects on other fundamentals.

5.1 Measuring Commuting Effects

Taking logs and rearranging Equation (1) yields:

$$\ln(N_{ij}) = \ln(\bar{N}) - \epsilon\ln\left(\frac{\bar{V}}{\gamma_\epsilon}\right) + \ln\left(Q_i^{\epsilon(\zeta-1)}B_i\right) + \ln(W_j^{\epsilon}E_j) + \epsilon\ln(\delta_{ij}) + \ln(D_{ij}),$$

Defining $\theta_i = \ln(Q_i^{\epsilon(\zeta-1)}B_i)$, $\omega_j = \ln(W_j^{\epsilon}E_j)$, $g_0 = \ln(\bar{N}) - \epsilon\ln\left(\frac{\bar{V}}{\gamma_\epsilon}\right)$, and noting that $\ln(D_{ij})$ functions as a residual, this becomes

$$\ln(N_{ij}) = g_0 + \theta_i + \omega_j + \epsilon\ln\delta_{ij} + \underbrace{\eta_{ij} + \ln(D_{ij})}_{\equiv d_{ij}}. \tag{9}$$

The commuting model thus delivers a tractable empirical estimating equation that depends on accessibility (δ_{ij}), fixed effects (which may subsume the constant g_0), and an error term (Section 5.2 extends this to panel data).

Measuring how transportation affects commuting can be accomplished in several ways. The most common approach is to calculate travel times and use those directly to fit the location choice model. Alternatives include embedding a mode choice model or a measure of exposure, proximity, or treatment. To unify notation, define

$$\delta_{ij} = \bar{\delta}_{ij} \exp(\eta_{ij}), \quad \bar{\delta}_{ij} = \begin{cases} \exp(-\kappa\tau_{ij}) & \text{for travel time with a single mode} \\ \sum_m \exp(u_m(-\kappa\tau_{ijm})) & \text{for travel times with multiple modes} \\ \exp(\beta T_{ij}) & \text{for a measure of treatment (exposure) to transit.} \end{cases}$$

This notation separates access into an observed component, $\bar{\delta}_{ij}$, and an unobserved component, η_{ij}. The observed component can be constructed from several pieces: τ_{ij} is the travel time from i to j and τ_{ijm} is its mode-m specific equivalent, κ is the marginal utility of travel time, u_m is a subutility function, and T_{ij} is a direct measure of exposure or treatment with effect β.

This framework defines two sources of potential endogeneity between observed accessibility, $\bar{\delta}_{ij}$, and flows N_{ij}. The first is unobserved or mismeasured travel times, in η_{ij}. Although potentially due to simple measurement error, this could also embed spillovers, such as congestion, or behavioral responses, like changes in departure times. Second, latent, route-specific factors, in $\ln(D_{ij})$, can also be problematic. Examples include scenic views, riskiness, or route complexity. Because these are not typically separable, I group them into the term:

$$d_{ij} \equiv \eta_{ij} + \ln(D_{ij}).$$

However, the many potential sources of endogenous response captured in d_{ij} underscore the need to validate the mapping from transportation infrastructure to flows, as discussed in Section 7.3.

From Travel Times with a Single Mode

Modern routing engines allow researchers to rapidly calculate travel times, τ_{ij}, under a wide variety of infrastructure and use scenarios. This lets the researcher easily obtain bilateral travel times based on the contemporaneous observed transportation network (e.g., Akbar et al. 2023). Using these travel times and substituting $\bar{\delta}_{ij} = \exp(-\kappa\tau_{ij})$ into Equation (9) yields:

$$\ln(N_{ij}) = g_0 + \theta_i + \omega_j - \epsilon\kappa\tau_{ij} + d_{ij}. \tag{10}$$

Travel times directly enter Equation (10).[15] However, there is insufficient variation in Equation (10) to separately identify ϵ from κ. To separate these parameters, the researcher must either make an assumption about the value of either κ or ϵ, or employ additional variation.

There are additional challenges. First, researchers face several degrees of freedom in the sampling process. They must determine whether to use a single point (typically the centroid) per

15. It is common for urban gravity (e.g., Equation 10) to be expressed as a function of linear travel time, whereas models of trade typically employ log travel time or distance.

geographical unit, or to sample multiple points.[16] They must also decide when in the day to sample travel times, as different times in the day may reflect different levels of congestion. Validation against experienced travel times is useful, but requires survey, GPS, or road-monitoring data. These choices all impact the interpretation of $\epsilon\kappa$.

From Travel Times with Multiple Modes

Alternatively, a mode choice sub-model can be used to capture accessibility and to estimate κ. The traveler can choose mode m from a set of modes, each of which has travel time τ_{ijm}. Assume that, conditional on choosing route ij, the traveler faces $U_{mo|ij} = \mu_m - \kappa\tau_{ijm} + \varepsilon_{ijmo}$, with ε_{ijmo} being idiosyncratic preferences distributed Type 1 Extreme Value. Then, the expected (or inclusive) value of the mode choice sub-model is captured by

$$I_{ij} = \mathbb{E}_o[\max_m U_{mo|ij}] = \ln\left(\sum_m \exp(\mu_m - \kappa\tau_{ijm})\right).$$

Substituting this expression into Equation (9) gives:

$$\ln(N_{ij}) = g_0 + \theta_i + \omega_j + \epsilon I_{ij} + d_{ij}. \tag{11}$$

This model is similar to Equation (10), but has one key difference. The marginal disutility of travel time, κ, is estimated using variation in travel times across modes, and so estimates of ϵ can be obtained directly from Equation (11).

The mode choice sub-model is typically estimated independently or as an early recursive step. Implicitly, this assumes recursive decision making by the agent: While uncertain about ε_{ijmo}, the agent chooses where to live and work. Then, they realize their idiosyncratic mode preference and choose the mode that maximizes their utility conditional on i and j. The sub-model could be even richer, such as featuring nested mode decisions (as in Tsivanidis 2026) or routing decisions (as in Allen and Arkolakis 2022), and Allen, Fuchs, and Wong (2025) (in this volume) build on Fuchs and Wong (2024) to incorporate multiple modes and routes. As these papers show, any discrete choice model of travel that conditions on origin and destination could be used to further enrich the notion of access.

16. Some care should be taken in this stage; e.g., some centroids may lie in inaccessible locations. Special care should be taken when calculating the time from i to i; these are unlikely to be zero. Researchers can sample multiple points, include an additional indicator and parameter $\epsilon\kappa^{\text{local}}\mathbb{1}[i=j]$, include the average distance from the centroid to the edge as a control, or the root of area.

Directly from Treatment

Alternatively, access may directly measure exposure to infrastructure. For example, let $\ln(\bar{\delta}_{ij}) = \beta g(d_s(i), d_s(j)) = \beta T_{ij}$ measure the proximity of i and j to transit (i.e., where $d_s(x)$ is the distance from x to the nearest transportation station, s).[17] Under this assumption, substituting into Equation (9) gives:

$$\ln(N_{ij}) = g_0 + \theta_i + \omega_j + \epsilon\beta T_{ij} + d_{ij}. \tag{12}$$

As in the case of the single-mode model, Equation (12) only recovers the compound parameter $\epsilon\beta$. However, a benefit of this model is that it may be possible to interpret $\tilde{\beta} \equiv \epsilon\beta$ as a treatment effect.

The primary benefit of this approach is that it directly measures the response of commuting flows to transportation infrastructure. In contrast, the other approaches infer the changes in commuting flows from changes in times in conjunction with other parameters. This implicitly assumes that commuting flows respond to the changes induced by the transportation infrastructure under study in precisely the same way they do to all other changes in travel times. In practice, this may or may not be a reasonable assumption; see the discussion in Section 7.3.

5.2 Identifying Commuting Effects (and Practical Estimation Details)

The gravity equation contains the primary parameters that govern how transportation impacts commuting, so identifying these parameters is necessary for a causal interpretation of gravity. Fortunately, the gravity models in Equations (9)–(12) can accommodate panel data, instrumental variables, or both. This suggests several approaches for identifying effects, with many papers opting for several designs to build confidence in the robustness of estimates. I pay special attention to gravity parameters as identification of other QSM parameters follows standard methods.

The panel gravity model conditions on time-invariant residential location-by-workplace fixed effects, in addition to residential location-by-time and workplace-by-time fixed effects (which absorb the period-specific intercept, g_{0t}, in estimation):

$$\ln(N_{ijt}) = g_{0t} + \theta_{it} + \omega_{jt} + \mu_{ij} + \epsilon \ln \bar{\delta}_{ijt} + d_{ijt}. \tag{13}$$

Location pair fixed effects, μ_{ij}, control for confounding factors specific to ij that determine flow and do not change during the sample. Some examples include persistent workplace-residential sorting, consistent unmodeled congestion or transit, or commuter preferences for unobserved but complementary characteristics between work and residential locations.[18]

17. Unlike typical measures of treatment based on a single distance, this measure should explicitly capture proximity of *both* i and of j to the transportation improvement. Thus, it may impose some symmetry of treatment on origins and destinations.

18. However, μ_{ij} also absorbs time-invariant factors for which the researcher may want to estimate effects, such as distance or travel time (when only a single cross-section of travel times are available).

This enables using difference-in-difference (DD) or staggered-adoption designs to identify transportation effects, as in Gaduh, Gračner, and Rothenberg (2022). Credibility depends on whether untreated location pairs can serve as plausible controls for treated location pairs. The reasonableness of this identifying assumption varies substantially across settings. However, even without additional arguments or restrictions, panel gravity settings offer their own refinements that may plausibly aid identification. Because of the dyadic structure of Equation (9), a particularly relevant control set is units common to treated pairs, but not both treated. For a treated pair ij, the set of pairs $i'j$ and ij' for $i \neq i'$ and $j \neq j'$ is particularly likely to reflect some similar counterfactual evolution of commuting patterns. This *common units* approach is implemented in Severen (2023).

Planned but unbuilt, partially built, or not yet built networks offer an alternative set of control pairs. Location pairs lying along planned routes may have been particularly likely to have been treated, yet were not (or were not yet) treated. Several papers adopt this approach. Tsivanidis (2026) uses planned but unbuilt lines to define a control group in Bogotá, while Zárate (2023) uses a not yet built line to create a placebo for a line that was built in Mexico City. Severen (2023) uses a historical planned subway network from the 1920s to develop an additional plausible control group for Los Angeles' subway build out, which began to open in the 1990s.

The gravity model can also accommodate an instrumental variables (IV) approach to address omitted variable bias. It is common to instrument travel time with distance, though the credibility of this approach depends on the particular research setting. More promising is the use of inconsequential units designs, wherein treatment can be instrumented by whether a route lies along the lines connecting two important locations. Tsivanidis (2026) uses a least-cost routing algorithm to develop an instrument for bus rapid transit routes that prioritize connecting transit portals to the urban core. Tyndall (2021) notes that many cities prioritize connecting airports to their cores and uses this to develop an inconsequential units-type instrument (cf. Redding and Turner 2015).

Researchers often face a choice in whether to use historical transportation infrastructure data to develop an IV design or to refine the control group in DD designs. Generically, for treatment T_i, error u_i, potential instrument or conditioning variable Z_i, and selection equation s, this is a choice between assuming $\mathbb{E}[\Delta Z_i \Delta u_i] = 0$ (IV) or $\mathbb{E}[\Delta T_i \Delta u_i | i \in s(T_i, Z_i)] = 0$ (DD). While the better assumption is setting specific, it is important to note that IV exclusion restrictions based on a historical network effectively limit any independent role of persistence in urban form. Consider Brooks and Lutz (2019), who find that locations historically served by tramways remain denser than nearby locations that were not. If the density or character of these locations has an independent influence on commuting patterns outside of how it impacts current transportation systems, then the IV design is invalid.

Practical Issues for Gravity (Commuting) Estimation

Consider Equation (9) and its descendants in Equations (10)–(12). A first concern is that $\ln(N_{ij})$ is undefined if $N_{ij} = 0$. If this is true for any ij, then estimation using the full sample is infeasible and estimation using ordinary least squares (OLS) on flows with $N_{ij} > 0$ generates bias by selecting the sample based on the outcome. This can be overcome through the use of the Poisson pseudo-maximum likelihood (PPML) estimator, which posits the relationship:

$$\mathbb{E}[N_{ij}] = \exp(\theta_i + \omega_j + \epsilon \ln \bar{\delta}_{ij}), \tag{14}$$

where the expectation is over the error in ij flows. Importantly, the PPML estimator delivers consistent estimates even if the distributional assumption is incorrect, much like OLS.[19] This means that even if N_{ij} is scaled so as to contain non-integer values, PPML will continue to provide consistent estimates when correctly specified.[20] Sotelo (2019) notes a related issue. Equation (9) can be rewritten as conditional shares, e.g., $\pi_{ij|i}$ or $\pi_{ij|j}$. Doing so can remove the need to include one dimension of fixed effects. However, this also reweights the contribution of each ij pair, such that the weights are equal for the flows across the conditioned-upon dimension.

Second, there may be substantial granularity if units are at a small level of disaggregation, with N_{ij} predominantly taking the value of small non-negative integers. For estimating models like Equation (9), this may just inflate standard errors. However, granularity can play a much more substantial role in simulating model equilibria, and thus can drive substantial variation in counterfactual estimation (Dingel and Tintelnot 2026).

5.3 Endogenizing Travel Times

This model assumes that travel times are determined exogenously. However, a variety of factors can shift travel times, and these factors are likely to respond to changes in transportation infrastructure. Two leading examples are congestion and private transit provision.

There are several ways to incorporate congestion into the QSM framework. The most straightforward is to directly parameterize travel times as a function of the number of travelers from a location to a destination. However, such an approach misses the effects of funneling flows onto particular roads regardless of the origin and destination. In contrast, Herzog (2024) carefully cumulates traffic along fixed routes to approximate the total traffic load that a commuter encounters between their residence and workplace in order to understand how traffic changes in response to a congestion charge cordon. Somewhat more simply, Severen (2023) estimates the relationship

19. Bellégo, Benatia, and Pape (2022) propose another solution to the so-called "log of zero" problem (Silva and Tenreyro 2006).

20. In panel gravity applications with several periods and staggered treatment adoption, traditional estimators may estimate biased treatment effects due to contamination (e.g., Goodman-Bacon 2021). Nagengast and Yotov (2025) consider how to address heterogeneous treatment effects with staggered treatment adoption using the PPML estimator.

between transit and changes in automobile congestion by regressing changes in travel times on the share of the fastest route between two locations that is exposed to newly constructed rapid transit (i.e., lies within a corridor around transit).

As an alternative to methods that fix routes, it is possible to endogenize route choice. Allen and Arkolakis (2022) implement a route choice problem that is nested with the standard QSM framework. Agents receive idiosyncratic preference shocks for routes, and so route selection becomes a probabilistic function of travel times and preferences. With these probabilities, the expected traffic on any segment can be calculated, and then its contribution to congestion estimated or calibrated. By permitting infinitely long routes, this distributional assumption delivers tractable matrix expressions that reflect congestion. Estimates typically suggest a high degree of substitutability between routes (Allen and Arkolakis 2022; Hwang 2024). However, a conceptual challenge with this framework is that it does not always accord with how people select routes, wherein they typically consider a much smaller choice set of candidate routes. Moreover, travelers often take suboptimal routes for unmodeled reasons that may be difficult to rationalize with extreme-value idiosyncratic errors (Larcom, Rauch, and Willems 2017).

Another motivation for endogenizing travel time is to study the supply of transportation. Bordeu (2024) extends the Allen and Arkolakis (2022) framework by allowing fragmented governments within a city to decide how much roadway to provide, thus impacting congestion. Because congestion spills over beyond municipal borders, roadways are underprovided, particularly near the edges of municipalities. Endogenizing transportation supply is particularly vital when infrastructure is less durable. For example, formal public rapid transit systems provide networks that are relatively fixed and durable, while the informal private transit provision common in much of the world can evolve much more quickly and fluidly. These systems endogenously provide transit as bundles of travel times and prices by varying routes and waiting times. Conwell (2026) considers the incentives to provide high-quality travel services of associations of private transit providers. Indeed, these two papers demonstrate that QSMs are as useful for learning about the endogenous supply of transportation as the demand for transportation.

5.4 Measuring Non-Commuting Effects

Transportation infrastructure can also directly impact non-commuting fundamentals, like productivity or amenities, or be accompanied by policies that impact such fundamentals.

Viewed through the lens of the QSM, changes in prices and quantities are endogenous to changes in transportation infrastructure. Accordingly, model-consistent methods of measuring non-commuting impacts seek to recover the effects of transportation infrastructure on the fundamentals embedded in the QSM, i.e., the terms $\{A_i, B_i, C_i, E_i\}$. To make this plain, taking logs of

Equation (3), Equation (4), and the fixed effects in Equation (9) gives the linear system:

$$
\begin{aligned}
\text{Labor demand:} \quad & \ln(W_i) = (\alpha-1)\ln(N_{Fi}) + (1-\alpha)\ln(L_{Fi}) + \ln(A_i) \\
\text{Labor supply:} \quad & \omega_i \;\; = \epsilon \ln(W_i) + \ln(E_i) \\
\text{Housing demand:} \quad & \theta_i \;\; = \epsilon(\zeta-1)\ln(Q_i) + \ln(B_i) \\
\text{Housing supply:} \quad & \ln(Q_i) = \psi \ln(H_i) - \psi \ln(L_{Ri}) + \ln(C_i),
\end{aligned}
$$

where constant terms have been omitted.[21] The fundamentals are clearly playing the role of empirical residuals in this system of equations.

This system, along with Equation (9) and the market clearing conditions, fully describes the urban economy. Because this model is uniquely invertible, the fundamentals are calculable from observed data and the parameter vector $\{\alpha, \epsilon, \zeta, \psi\}$. With these fundamentals in hand and some measure of exposure, proximity, or treatment at each location i, denoted T_i, it is possible to estimate auxiliary models, like:

$$\mathbf{Y}_i = \boldsymbol{\lambda} T_i + \mathbf{u}_i, \tag{15}$$

where $\mathbf{Y}_i = \{\ln A_i, \ln B_i, \ln C_i, \ln E_i\}$ are the fundamentals recovered above and $\boldsymbol{\lambda} = \{\lambda^A, \lambda^B, \lambda^C, \lambda^E\}$ reflect the impacts of T_i; $\mathbf{u}_i = \{a_i, b_i, c_i, e_i\}$ are residuals. Sometimes, $\{\ln A_i, \ln B_i, \ln C_i, \ln E_i\}$ are deemed endogenous fundamentals and $\{a_i, b_i, c_i, e_i\}$ exogenous fundamentals. Alternatively, T_i could be a more flexible function of other endogenous variables. As a result, this representation is conformable to agglomerative spillover terms, such as those in Ahlfeldt et al. (2015).

5.5 Synthesizing Approaches

The alternative approaches to QSMs presented in Section 2 can now be interpreted through the lens of QSMs. Table 1 shows how these methods typically interpret the effect of transportation infrastructure, and then describes the target estimand of each approach. The next column provides a mapping from each method's interpretation of transportation effects into a form consistent with the QSM, and the last column derives an estimating equation from the QSM of Section 4 that reflects each method.[22] These estimating equations can then be employed with standard quasi-experimental research designs, offering several sources of identification. Although the estimating equations are particular to this QSM, similar results can be obtained for most models.

A key observation from Table 1 is that hedonic and sorting models often treat transportation infrastructure as an amenity, rather than explicitly modeling changes in mobility.[23] However, hedonic methods measure responses in prices, whereas sorting methods measure population (quantity) responses. Supposing that the amenity (or disamenity) effect of transit is captured by Equation

21. Note the presence of the land use terms even though they are taken as exogenous.

22. Derivations are in the Appendix, including residential market access, $\mathcal{W}_i$, and average residential wage, $\bar{w}_i$.

23. In fact, a growing body of research shows that infrastructure affects both mobility and amenities; see Section 6.2.

(15), i.e., $\ln B_i = \lambda^B T_i + b_i$, hedonic estimates of transportation effects can be interpreted as

$$\frac{\partial \ln Q_i}{\partial T_i} = \hat{\epsilon}\lambda^B,$$

where $\hat{\epsilon} = \psi/(1+\psi(\epsilon(1-\zeta)+1))$ is a function of the QSM's parameters. Hedonic analysis reflects equilibrium in the housing market, but treats labor market factors as fixed. Because of this, hedonic partials $\frac{\partial \ln Q_i}{\partial T_i}$ incorporate housing supply responses but treat other factors (e.g., $\mathcal{W}_i$) as fixed. In contrast, Table 1 shows that sorting models interpret transportation effects as

$$\frac{\partial \ln \pi_{Ri}}{\partial T_i} = \lambda^B.$$

Because sorting analysis is often partial equilibrium, the partials $\frac{\partial \ln \pi_{Ri}}{\partial T_i}$ treat all response margins (except population adjustment) as fixed.

The estimating equation also reveals what the QSM views as potential sources of endogeneity. For the hedonic method, these include residential income and market access ($\bar{\omega}_i \mathcal{W}_i$), inverse construction productivity (C_i), residential land supply (L_{Ri}), and other amenities (b_i). For the sorting approach, housing prices Q_i take the place of residential income, land supply, and housing productivity. In both cases, panel data may permit i-area fixed effects that can control for some of these differences. This synthesis also shows that QSMs can also be informative for non-QSM reduced form analysis.

Finally, Table 1 also includes travel demand analysis, which usually has a narrower scope. A typical application takes the quantity of travel from i to j as fixed and seeks to calculate the value of adding a new mode (or perhaps improving the time of an existing mode). This results in a discrete choice problem, which is typically treated as a logit model and estimated to recover the disutility of travel time, κ, and mode-specific utility shifters.[24] The expected value of this problem is I_{ij}, which then enters as in Equation (11).

5.6 Parameter Interpretation, Labels, and SUTVA Violations

A key motivation for evaluating urban transportation with QSMs is that transportation treatments (i) may directly impact many, or even all, of the locations within a city, and/or (ii) may indirectly alter outcomes across a city via general equilibrium effects. Both motivations lead to violations of SUTVA, which complicates interpretation of parameter estimates based on quasi-experimental techniques.[25]

24. Though, taking logs can generate a linear estimating equation, just as in Equation (9).

25. For example, Diamond and Serrato (2025) note that a logit-type location choice model violates SUTVA, and so the choice probabilities for locations should be differenced. This resolves the SUTVA violation by changing the outcome being modeled (i.e., to the log difference in the likelihood of choosing one place relative to another). It does not, however, change the *point estimate* of the parameter value, which can be consistently estimated without differencing.

Table 1: Interpreting Hedonics, Sorting, and Travel Demand Methods in a QSM

Method	Treatment Type & Measurement	Target Estimand	Interpretation of Treatment in QSM	Estimating Equation Consistent with QSM
Hedonics	Proximity to station: T_i	$\frac{\partial \ln Q_i}{\partial T_i}$	Residential amenity: $\ln B_i = \lambda^B T_i + b_i$	Housing price regression: $\ln Q_i = \tilde{\epsilon}\lambda^B T_i + \tilde{\epsilon} \ln(\bar{w}_i \mathcal{W}_i) + \frac{\tilde{\epsilon}}{\psi} \ln C_i - \tilde{\epsilon} \ln L_{Ri} + \tilde{\epsilon} b_i$
Sorting	Proximity to station: T_i	$\frac{\partial \ln \pi_{Ri}}{\partial T_i}$	Residential amenity: $\ln B_i = \lambda^B T_i + b_i$	Residential population regression: $\ln \pi_{Ri} = \lambda^B T_i - \epsilon(1-\zeta) \ln Q_i + \ln \mathcal{W}_i + b_i$
Travel demand	New mode m connecting ij, travel time: τ_{ijm}	$\frac{\partial I_{ij}}{\partial \tau_{ijm}}$	Accessibility index: $\bar{\delta}_{ij} = I_{ij} = \ln \left(\sum_{h \in \mathcal{M}} e^{\mu_h - \kappa \tau_{ijh}} \right)$	Logit mode choice regression: $\pi_{m\|ij} = \frac{e^{\mu_m - \kappa \tau_{ijm}}}{\sum_{h \in \mathcal{M}} e^{\mu_h - \kappa \tau_{ijh}}}$

Note: This table interprets the methods in Section 2 through the lens of the QSM of Section 4; derivations are in the Appendix.

Equation (9), by definition, violates SUTVA. In a potential outcomes framework, SUTVA requires that changes in the value of treatment for one observational unit do not directly impact the potential outcomes of another unit. The constant g_0 in Equation (9) implicitly embeds the expected utility term $\bar{V}$, which itself depends on the entire matrix δ_{ij}. Thus, shifting δ_{ij} impacts the value of $N_{i'j'}$ for $i, j \neq i', j'$ (through g_0). If SUTVA is violated, parameters (including, e.g., ϵ, ψ, and κ) do not represent elasticities or semi-elasticities, and $\tilde{\beta} = \epsilon\beta$ in Equation (12) no longer represents a treatment effect.

However, SUTVA violations do not impact whether these coefficients can be consistently estimated. Moreover, these parameters are still informative about partial equilibrium elasticities and treatment effects. Consider the relationship between Equation (1) with single-mode travel times ($\bar{\delta}_{ij} = \exp(-\kappa\tau_{ij})$) and Equation (10). In partial equilibrium, the derivative of (1) with respect to τ_{ij} is:

$$\frac{d\ln(N_{ij})}{d\tau_{ij}} = -\epsilon\kappa(1 - \pi_{ij}) = -\epsilon\kappa\left(1 - \frac{N_{ij}}{\bar{N}}\right).$$

In contrast, the derivative of Equation (10) gives

$$\frac{\partial\ln(N_{ij})}{\partial\tau_{ij}} = -\epsilon\kappa,$$

if conditioning on g_0.[26] Recalling that g_0 represents the log denominator of (1) reconciles the differences between these derivations. Accordingly, $\epsilon\kappa$ govern the strength of the semi-elasticity of commuting flows with respect to travel times, but the actual semi-elasticity is $-\epsilon\kappa(1 - \pi_{ij})$.[27] However, this does not impact the potential validity of, e.g., Equation (10) to provide valid estimates of $\epsilon\kappa$.

This distinction between parameters and treatments or elasticities is somewhat semantic in partial equilibrium, but becomes substantive in general equilibrium. In partial equilibrium, a change in travel times, say from τ_{ij} to τ'_{ij}, only impacts flows directly; it does not propagate through price changes. In general equilibrium, however, it does propagate, and so the shift in $\ln(N_{ij})$ changes wages and housing prices, which then cause further changes in populations, etc. Consistent parameter estimation with general equilibrium forces typically requires some additional exogenous variation, often in the form of an instrumental variable.

The notion of an elasticity or treatment effect in general equilibrium may still be valid but must rely on the model's structure to evaluate. In fact, this is an interesting area for investigation. Monte, Redding, and Rossi-Hansberg (2018) estimate heterogeneous county-level labor supply elasticities reflecting differences in nearby geography and populations, despite a single param-

26. The Appendix also derives an approximation of this for a discrete treatment using Equation (12).

27. In practice, shares are quite small, so true elasticities and effects will be close to the estimated parameters. Given this, the shorthand practice of referring to these as elasticities or treatment effects is not unreasonable, as long as careful analysis preserves the distinction.

eter corresponding to the household's labor supply. Relatedly, Baum-Snow and Han (2024) use variation partially induced by differential economic geography to estimate local-area elasticities of housing supply.

6 QSM-Based Evidence on the Effects of Transportation Infrastructure

QSMs have been deployed to study a growing set of transportation improvements. This section synthesizes the conclusions of these efforts, grouping discussion first into commuting effects—changes in travel time to work, residential location, and workplace—before then considering other effects, including those more downstream. This distinction is partly because canonical urban QSMs focus on separating work and residential locations but also because data on commuting are more prevalent than data on other types of mobility.

6.1 Commuting Effects

The value of travel time savings (VTTS) can capture substantial benefits of transportation infrastructure, but only reflects a portion of total effects. Comparing VTTS with welfare measures from QSMs to study the large expansion of BRT in Bogotá, Tsivanidis (2026) finds that incorporating residential and workplace mobility increases calculated welfare by 21% over VTTS ignoring productivity and amenity spillovers and by 85% when including these spillovers. These results show that the changes in bilateral access wrought by transit substantively alter the matching between residential locations and workplaces, and that these changes are quantitatively important. Moreover, accounting for economic spillovers can have a multiplicative effect on the implied welfare gains.

Indeed, relocation is an important margin that is typically essential for large welfare effects. Transit, in particular, concentrates employment in central districts, allowing many more workers to reach firms. Transit lets firms benefit from increased productivity through agglomeration without losing access to labor. This drives up land and floorspace prices in central areas, leading to a decline in the residential share of floorspace. While this was transformative in historical settings (e.g., Heblich, Redding, and Sturm 2020), it is still relevant in modern settings where transit is sufficiently impactful (Tsivanidis 2026).[28] In contrast, car-serving highways decentralize employment as well as residences, though residential decentralization is greater (Baum-Snow 2020). In part, this may be because highways generate barrier disamenities that decrease the desirability of central and near-central areas they pass through (see Brinkman and Lin 2026, in this volume).

For transit, welfare effects depend on the size and implementation of the intervention and the availability of alternatives (like cars and mopeds). Gaduh, Gračner, and Rothenberg (2022)

28. Delventhal, Kwon, and Parkhomenko (2022) find that work-from-home shocks also change the within-city distribution of economic activity, concentrating employment and dispersing residences.

find that the early stages of BRT in Jakarta had minimal effects, largely because the BRT was not sufficiently separated from other modes and so led to a substantial increase in congestion.[29] And Severen (2023) finds substantial commuting effects of transit connections: neighborhoods in Los Angeles connected by rail see commuting flows increase by 15% within ten years and by 25% within twenty-five years. However, these effects do not aggregate into a large overall impact; welfare effects are 20-40 times larger for the Bogotá system than Los Angeles'. The difference is in large part driven by the relative attractiveness of the automobile and the infrastructure that supports driving. In Los Angeles, extensive highways enable fast automobile trips relative to transit and higher incomes support widespread automobile adoption. In Bogotá, roughly 36% of commuters used the BRT and it had 2.2 million trips/day, while in Los Angeles fewer than 1% of commuters used LA Metro Rail and it had, at most, 150k trips/day (Severen 2023).[30]

6.2 Other Effects and Downstream Consequences

A growing literature incorporates more diverse channels through which transportation can impact urban economic geography, leading to several interesting throughlines.

Land-use policy and housing supply are important mediators—or inhibitors—of transportation benefits. For example, Anagol, Ferreira, and Rexer (2021) show that zoning changes targeted at increasing density along transportation corridors substantially lowered housing prices and expanded transit access in São Paulo. Chen et al. (2024) consider transit oriented development and find that combining subway expansions with densification substantially increases resident welfare over subway expansions alone. In a more nuanced conclusion, Hu and Wang (2025) suggest that Beijing's zoning underdevelops land near subways in the urban core and overdevelops land near suburban stations.[31] And both Tsivanidis (2026) and Severen (2023) find that liberalizing land use near stations would have substantially increased the value of new rapid transit networks.

Amenity (or disamenity) effects of transportation infrastructure, and particularly highways, can be empirically important and change aggregate and distributional conclusions. Brinkman and Lin (2024) demonstrate that highways reduce nearby residential amenities; that is, highways cause B_i to decline for i near the highway. These disamenities interact with and can exacerbate racial differences (Bagagli 2025; Weiwu 2025). Given the substantial impact that infrastructure can have on the built environment, this type of research seems particularly important for understanding urban dynamics.

29. More recent improvements in system operation improve BRT desirability (Kreindler et al. 2026).

30. There is a methodological difference: Severen (2023) defines as treated only pairs of neighborhoods both within a few hundred meters of a rapid transit station, while Tsivanidis (2026) uses a market access approach. With market access, all neighborhoods see at least some improvement in travel time to some destinations, and so the transit effects spread over a larger area, even absent general equilibrium considerations.

31. See also Garcia-López, Sanchis-Guarner, and Viladecans-Marsal (2026) in this volume for a broader discussion of the links between transportation and housing.

The sorting and segregation studied in Bagagli (2025) and Weiwu (2025) represent an endogenous neighborhood amenity, the local residential composition. Although those studies focus on race, the education mix of a neighborhood can play a role in neighborhood evolution. Tsivanidis (2026) incorporates heterogeneous types by education, with an endogenous residential amenity that reflects the high-education share of the neighborhood population. Warnes (2024) extends this by adding dynamics. An intriguing avenue of study is to provide evidence distinguishing different microfoundations for these amenity terms. A good example of this is Khanna et al. (2023), who use a QSM to isolate specific amenity channels and show that improved transportation access increases economic opportunity and reduces overall crime, despite dispersing crime to different locations.[32] Pollution from mobile transportation sources is also a disamenity that can drive household sorting (Ubeda 2024).

There has been somewhat less of a focus in studying the direct local productivity effects of transportation (beyond agglomeration).[33] Many QSMs retain the relatively simple production structure that comes with either an assumption of perfect competition or monopolistic competition. Pérez, Vial, and Zárate (2022) relax that structure, instead allowing local firms to function as oligopolies. This modeling assumption leads to a finding of pro-competitive effects of transit expansions. In a somewhat related finding, Zárate (2023) builds a QSM with both informal and formal employment and shows that rapid transit expansions can shift informal employment to the formal sector. These papers highlight that nuances in the interactions between transportation and labor markets can have substantive welfare impacts, particularly in large cities where travel costs constrain access and economic activity.

Consumption (and other non-commuting) travel and the presence of multi-person households can also meaningfully change the incidence and welfare effect of infrastructure. Miyauchi, Nakajima, and Redding (2025) incorporate both consumption travel and trip chaining into the QSM framework to study consumption patterns in greater Tokyo, and find that excluding consumption travel leads to undervaluing the effects of improved transit. Combining travel card data from Singapore with variation in a subway line opening, Lee and Tan (2024) also consider consumption travel and show that ignoring consumption travel dramatically understates heterogeneity in the effects of the subway expansion across income groups. Velásquez (2023) develops a QSM in which some households have multiple workers. These workers have heterogeneous preferences for commuting, as may be due to different (gendered) roles within the household (e.g., Le Barbanchon, Rathelot, and Roulet 2021; Liu and Su 2024). Residential location choice thus balances these differing preferences (or expectations). Similarly, Pietrabissa (2023) builds a model that reflects

32. Ang, Angel, and Parkhomenko (2024) report that a large combination of observed local characteristics can explain about 45% of estimated amenity fundamentals for a simple QSM in a large US county. While this suggests that modeling amenities as endogenous is well founded, it is also a warning that amenity fundamentals reflect other variation that may, or may not, accord with beliefs about what amenities represent.

33. Although they do not use a QSM, Koh, Li, and Xu (2025) show that subways facilitate local collaborations for patent development, suggesting future productivity effects.

parents' trade-offs between work and children's school access.

7 Frontiers and Shortcomings

Despite the manifold appeal of QSMs in modeling the effects of urban transportation infrastructure, they are not a panacea. I summarize two areas of recent growth that enrich the static homogeneity of early QSMs. Incorporating heterogeneity and dynamics enables new directions of research and better reflect reality, but such innovations risk becoming daedalian. I then turn to three areas of persistent shortcoming in the application of QSMs to urban transportation infrastructure. I present both frontiers and shortcomings together as they tend to be interrelated. Note, also, that while these comments are targeted primarily at transportation settings, they may apply more generally to the implementation of QSMs in other contexts.

7.1 Incorporating Heterogeneity

Standard QSM implementations feature agents that are identical (up to an idiosyncratic preference shock). This model can be extended through multiple discrete types of agents that are distinguished by a predetermined characteristic. Unfortunately, commuting data often do not reflect such differences, and an active area of development focuses on incorporating such differences into QSMs. Using cell phone data, Kreindler and Miyauchi (2023) propose two methods of mapping flows to skill heterogeneity based on the skill share at a residential location. However, a central challenge of such methods is that determinants of commuting probabilities do not retain attractive analytic formulae when aggregated (Redding and Weinstein 2019).

If the distribution of skill (or other characteristics) at residence and at work are separately observable, and commuting behavior can be modeled separately by group (such as in travel survey microdata), analysis can proceed without aggregating across types. Tsivanidis (2026) builds a full panel QSM based on such an insight. This model reflects the varied and non-homothetic preferences of higher- and lower-skill workers across locations, travel times and modes, and housing prices, and incorporates endogenous amenities and productivity. If such a feature is unobserved, it is still possible to incorporate non-homothetic preferences. Deffebach et al. (2025) and Rollet (2025) assume a population-wide distribution of skill, and then fit the model by probabilistically assigning households to different nodes of the skill distribution. These developments suggest richer integrations with latent class modeling techniques.

However, QSMs have so far avoided more general forms of heterogeneity, generally falling short of the richness captured in residential sorting models (e.g., Almagro and Domínguez-Iino 2025). A first-order concern is that locations may have more heterogeneity in substitution patterns than permitted by the distributional assumptions underlying QSMs. Households likely only consider a few neighborhoods when deciding where to live (Piazzesi, Schneider, and Stroebel 2020).

There is also much unmodeled sorting by sector and occupation into workplaces. Some of this can be addressed by nesting groups of neighborhoods together, as in Alves, Burton, and Fleitas (2025), though it is unclear ex ante how best to group neighborhoods in general.

7.2 Dynamics

QSMs have conventionally been static, even when estimated with panel data. Spatial adjustment is rarely instantaneous: households face moving costs, firms face relocation and job posting expenses, and buildings and infrastructure are durable goods that can take years to build and are subject to depreciation. In addition to reflecting economic processes, adding dynamics to QSMs can have additional benefits. Accounting for history can offer cleaner identification relative to static models. Conditioning on prior location (or moving costs) better quantifies the demand for access or the supply of labor to particular locations (Bayer et al. 2016; Diamond 2016). Warnes (2024) builds a QSM using data in Buenos Aires, thus accounting for moving frictions while measuring how households respond to the introduction of bus rapid transit. History can also provide sources of exogenous variation that are useful in identifying economic forces (Heblich et al. 2025).

Panel data on individual agents can also enable more flexible incorporation of heterogeneity. When unobservable heterogeneity drives sorting, cross-sectional data is limited in its ability to separately identify the value of places from the heterogeneity in the agents in those places. Balboni et al. (2025) highlight the importance this can play, showing that linear controls for observable demographics do relatively little to reduce sorting-induced bias. Panel microdata can help overcome this in one of two ways. Choice experiments that condition on a prior or final location (or both) can strip away confounding variation if the conditioning set is a sufficient statistic for heterogeneity (Almagro and Domínguez-Iino 2025; Kreindler et al. 2026). Second, panel microdata enable recovering the distribution of latent characteristics or preferences, potentially allowing for an arbitrary degree of heterogeneity (Arcidiacono and Miller 2011). Applications of both approaches within a full QSM are still limited.

Finally, adding dynamics helps models tackle interesting questions in urban economics and economic geography related to path dependence and persistence (Lin and Rauch 2022). Takeda and Yamagishi (2024) provide an adaptation of the dynamic regional model in Allen and Donaldson (2020) to urban settings. They use the destruction of Hiroshima to suggest that the combination of agglomeration forces and expectations led to the city's recovery, and so suggest that path dependence drives the spatial distribution of population. Transportation infrastructure can often play such an anchoring role (Bleakley and Lin 2012; Brooks and Lutz 2019).

The tension is that dynamic models are often less intuitive, more data hungry, and require more computation than static models. An additional challenge comes from managing the role of forward-looking economic agents. Most dynamic models assume agents are myopic, and dynamics only emerge via history dependence in location or durable goods. More realistic forward-looking behavior can be included in QSMs, though the literature is only beginning to consider these richer models (see, for example, Greaney, Parkhomenko, and Van Nieuwerburgh 2025).

7.3 Validating Effects on Flows

Researchers do not always validate the causal link from transportation infrastructure to commuting flows. Instead, as discussed in Section 5.1, a common approach is to (i) estimate the marginal disutility of travel time from a cross-sectional gravity model or borrow an estimate from another setting, then (ii) combine that estimate with simulations of the changes in travel time induced by a transportation intervention.

This implicitly makes two strong assumptions. First, it presumes that commuters respond to the changes in travel time induced by treatment as they would any other change in travel time. This may or may not be reasonable, and depends substantially on the type of transportation infrastructure being studied. It rules out behavioral, unmodeled changes in travel behavior.[34] If, as is common, the travel time between two locations is taken as the minimum or average of times across all modes, this implicitly ignores differences in the disutility of travel time across mode and differences in the average utility or accessibility of each mode. That is, it may not be reasonable to equate the marginal disutility of travel time for car travel, for walking, and for rapid transit. Moreover, if changes in travel time are instrumented, a similar observation applies to the local average treatment effect. The changes in travel time induced by the instrument may, or may not, represent a broader average marginal disutility of travel time.

Second, this approach assumes that the way in which people respond to changes in travel time is invariant to the temporal scale under study. In fact, this elasticity (or semi-elasticity) must always reference some time frame over which a reaction can occur. If a commuter's travel time increases by 30 or 60 minutes, they are unlikely to respond by immediately changing their residence or workplace. In fact, such responses can take rather a long time to play out. In part, this is because commuting flows likely embed latent sorting that can take substantial time to respond. This may be the case if, for example, the pair fixed effects in Equation 13 contain substantial explanatory power.

A leading alternative is to directly estimate the effects of (some measure of) treatment on flows. For example, with panel data on commuting flows, it may be credible to interpret the coefficient estimated by regressing flows on (changes in) proximity to treatment as a causal average treatment effect. This is the approach of Gaduh, Gračner, and Rothenberg (2022) and Severen (2023). Another example is Tyndall (2025), who directly estimates the effects of ferry connections in New York City using a panel gravity model.

34. A growing literature documents a surprisingly diverse set of responses to changes in transportation environments (just a few of many: Simonsohn 2006; Anderson et al. 2015; Larcom, Rauch, and Willems 2017; Severen and Van Benthem 2022; Kreindler 2024; Kreindler et al. 2026).

7.4 Parameters Reflect Inconsistent Temporal or Spatial Variation

QSMs rely on many parameters and, much like the witches' brew in Shakespeare's *Macbeth*, these parameters are often pieced together from various sources. Consequently, they may reflect behaviors at inconsistent temporal or spatial scales.[35] Economists have long been familiar with the idea that responses are more elastic in the long run than in the short run (e.g., Samuelson 1947; Milgrom and Roberts 1996). The short-run parameters estimated from a shock to transit provision (as in Anderson 2014) reflect a very different shock and temporal scale than those used to estimate labor or housing supply elasticities. Similarly, parameters estimated at one spatial scale may not port to another scale. To wit, if a parameter governing the dispersion of idiosyncratic preferences over residential locations is estimated from tract-level variation in Berlin, it is unlikely to be a reasonable parameter to study county-level residence choice in the United States.[36]

One particular case where this can occur is using, in the same model, a travel time disutility estimated from a cross-section of flows with other elasticities estimated from temporally-motivated shocks. The travel time disutility in this setting is best thought of as the long-run response to travel times. Other parameters, such as labor or housing supply and demand elasticities, are often estimated from more frequent (e.g., annual) variation. Perhaps such a time frame sufficiently approximates the long-run, perhaps not. Regardless, this matter is rarely discussed, even though it can play an important role in counterfactual estimation.

It is likely that the borrowing of parameters across research settings and papers exacerbates the ill effects of this witches' brew. However, in many settings, there may be little alternative. Though relatively parsimonious, QSMs still require a vector of parameters, many of which cannot be credibly identified in every single setting. In such cases, extensive testing of the sensitivity of model results and counterfactuals to alternative vectors is essential for the credibility of quantitative results. Given that these are *quantitative* spatial models, this would seem more essential than current practice often demonstrates.

Very tightly entwined with this issue is that parameters in QSMs often serve multiple roles, and thus wear many hats.[37] This can be both a feature and a source of challenges. For example, in the model presented in Section 4, the shape parameter ϵ is the elasticity of labor supply and the marginal utility of income, while also controlling the distribution of idiosyncratic preferences across locations and scaling the elasticity of housing demand (with respect to location). This embarrassment of riches suggests many ways to estimate the parameter, just as in Section 5.5.

35. In Shakespeare's Macbeth, the witches' brew is a jarring amalgamation of ingredients that seem at odds with each other (fillet of snake, wool of bat, howlet's wing, scale of dragon, and root of hemlock, among others). The purpose of this brew is to provide the protagonist with false visions and give a dangerous and unfounded sense of security about the future. This false information guides him to making rash decisions and committing rather unreasonable actions.

36. This relates to the modifiable areal unit problem (MAUP) in spatial statistics.

37. The transportation-obsessed titular character in Eastman's classic *Go, Dog. Go!* also tries on many hats, although with the goal of impressing guests at various social functions. Often, the hats are somewhat outlandish given the context of the event (Eastman 1961).

It is worth focusing specifically on the shape parameter, ϵ. This parameter is often borrowed across papers with quite different contexts despite the fact that it drives the scale of welfare changes in counterfactuals, as Equation (5) makes clear. For example, Tsivanidis (2026) finds that increasing the shape parameter by 55% in a homogeneous-type QSM with agglomeration forces decreases welfare by around 60%.[38] This suggests that, at minimum, researchers should regularly probe the robustness of quantitative conclusions to parameter choices when parameters are not local to the setting being researched. However, as Section 5.5 suggests, other moments may be readily available to estimate (or refine the calibration of) key parameters. In the case of transportation amenities, for example, Table 1 suggests that population changes can be used to identify amenity effects λ^B, which means that price changes can be used to identify $\hat{\epsilon}$ (and thus, ϵ, under additional assumptions).

7.5 Parameter, Counterfactual, and Model Uncertainty

Relatedly, many QSM implementations offer little quantification of uncertainty when evaluating counterfactuals. There are two concerning sources of uncertainty. The first is uncertainty over the magnitude of model parameters. Even if parameters are borrowed from other sources or calibrated, using only the point estimate to simulate model counterfactuals suppresses often significant uncertainty over parameter values. In models with many parameters, correlation in the uncertainty over these parameters can multiply. Ideally, sensitivity analysis should span the plausible subset of vector space covered by these parameters, though in practice this is unlikely to be feasible.[39] Severen (2023) and Tsivanidis (2026) both provide a structural bootstrap approach to address uncertainty in the joint distribution of key structural parameters for counterfactual exercises; broader use of indirect inference is also potentially useful (e.g., Faber and Gaubert 2019). Cocci and Plagborg-Møller (2025) offer a conservative method to incorporate parameter uncertainty under worst-case assumptions about correlation across parameters, even when parameters are borrowed. Bayesian methods may offer guidance.

Policy conclusions, such as addressing the cost effectiveness of historical transportation infrastructure, may shift once uncertainty is accounted for. Perhaps of even more concern, model behavior can change within the confidence region covered by model estimates. For example, the model in Allen and Donaldson (2020) exhibits a single steady state when evaluated at the point estimates for its spillover parameters, but when these spillover values are increased to the edge of their confidence region, the model exhibits multiple steady states.

A second source of uncertainty may be even more substantial: model uncertainty. The wide menu of choices available when constructing a QSM suggests that the researcher has a substan-

38. This mirrors the situation of the trade elasticity in international economics, which is widely copied across settings yet has a substantial influence on welfare (see, e.g., Simonovska and Waugh 2014).

39. Addressing estimation uncertainty in dyadic models is not trivial and applications of available methods (e.g., Graham 2020) are not widespread.

tial degree of freedom. This suggests that the QSM enterprise would be well served by placing more emphasis on model validation. Relatedly, a typical feature of QSMs is that they often perfectly rationalize the data used for quantification (more specifically, the fundamentals recovered from inversion perfectly reflect the data used for the inversion). Thus, in many cases, even an unreasonable model will provide an excellent fit of the data.

There are a few techniques researchers can draw on to boost confidence in the model and its implementation. One approach that would aid the credibility of these models is to report model assumptions (or ranges of parameters) that alter broad qualitative model conclusions. Knowing what in a model invalidates a conclusion is tantamount to knowing how the model recovers that result. In contrast, if every alternative modeling assumption and set of parameter values necessarily generate the same conclusion, then this conclusion is tautological with respect to the model and thus unhelpful for distinguishing various narratives for how the world works. A second approach is to report how the model performs at matching moments of the data that are untargeted in estimation or inversion. Of course, a researcher has a significant amount of freedom in choosing untargeted moments and so should avoid cherry-picking.[40]

8 Conclusion

QSMs offer an expansive paradigm to study how transportation infrastructure drives the evolution of urban economic geography. Despite this, it is often unclear which practices are best for the use of these models. Given that researchers often innovate on one or two model components while taking the rest of the model (including parameters) "off the shelf," we should work toward careful and conscientious implementation that reflects best practices. However, as a field, care should be taken to ensure that such progress in careful implementation and measurement does not stifle creative applications or extensions of these models.

In this review, I claim that QSMs are at their most compelling in evaluating urban transportation infrastructure when intimately linked with research design. Though this can take many forms, it will often consist of: well-identified causal links from infrastructure to travel costs, flows, or other fundamentals; locally appropriate elasticity estimation (or choice) that clearly maps fundamentals and equilibrium outcomes; and consideration of parameter and model uncertainty. QSMs are not a substitute for research design, and ignoring parameter identification risks losing internal validity and coherence.

The range of questions answered by QSMs, as well as the richness of the models themselves, is likely to continue growing. Spatially explicit data sources are ever more common, and a body of training and practice materials is making these models broadly accessible to researchers. We

40. The set of quantitative tools available to validate structural models is growing (e.g., Andrews, Gentzkow, and Shapiro 2020; Adão, Costinot, and Donaldson 2025).

should endeavor to ensure that these models be as transparent as possible and validate their use critically and carefully.

A Appendix

Derivation of Sorting and Hedonic Pricing Relationships

Expanding Λ_{ij}, Equation (1) can be written as:

$$\pi_{ij} \equiv \frac{N_{ij}}{\bar{N}} = \frac{W_j^{\epsilon} Q_i^{-\epsilon(1-\zeta)} \delta_{ij}^{\epsilon} B_i E_j D_{ij}}{\sum_r \sum_s W_s^{\epsilon} Q_r^{-\epsilon(1-\zeta)} \delta_{rs}^{\epsilon} B_r E_s D_{rs}}.$$

Define residential commuter market access as $\mathcal{W}_i = \sum_s E_s W_s^{\epsilon} \delta_{is}^{\epsilon} D_{is}$ and denote the denominator as $\Phi = \sum_r \sum_s W_s^{\epsilon} Q_r^{-\epsilon(1-\zeta)} \delta_{rs}^{\epsilon} B_r E_s D_{rs}$. Residential population can thus be written

$$N_{Ri} = \frac{\bar{N} Q_i^{-\epsilon(1-\zeta)} B_i \mathcal{W}_i}{\Phi}.$$

Suppose that amenities consist of transit proximity, T_i and other items u_i, such that $\ln B_i = \lambda^B T_i + b_i$ as in Equation (15). Then dividing both sides of the residential population equation by $\bar{N}$, substituting in the expression for $\ln B_i$, and taking logs permits deriving a relationship that accords with sorting models:

$$\ln \pi_{Ri} = -\epsilon(1-\zeta) \ln Q_i + \ln \mathcal{W}_i + \lambda^B T_i + b_i - \ln \Phi.$$

Thus, in partial equilibrium, a sorting model conformable to this QSM would recover a partial-equilibrium transportation effect of $\frac{\partial \ln \pi_{Ri}}{\partial T_i} = \lambda^B$.

For the hedonic relationship, both housing demand and supply must be considered. For housing demand, note that average wage in i is $\bar{w}_i = \sum_s \pi_{s|i} W_s$, and the total wages earned by i residents is $\bar{w}_i N_{Ri}$, and so housing demand can be expressed as:

$$H_i = (1-\zeta) \frac{\bar{w}_i N_{Ri}}{Q_i}.$$

Housing supply, derived in Equation (4), can be rewritten as:

$$H_i = \left(\frac{Q_i}{C_i} \right)^{\frac{1}{\psi}} L_{Ri}.$$

Market clearing equalizes demand and supply. Equating the two, substituting in the expression for residential population N_{Ri} derived above, and solving for Q_i gives:

$$Q_i = \left((1-\zeta) \frac{\bar{N} B_i \bar{w}_i \mathcal{W}_i C_i^{\frac{1}{\psi}}}{\Phi L_{Ri}} \right)^{\frac{\psi}{1+\psi(\epsilon(1-\zeta)+1)}}.$$

Again supposing that amenities consist of transit proximity, T_i and other items u_i, such that $\ln B_i = \lambda^B T_i + b_i$. Then, the hedonic pricing effect of a marginal change in transit proximity is

$$\frac{\partial \ln Q_i}{\partial T_i} = \frac{\lambda^B \psi}{1 + \psi \left(\epsilon(1-\zeta) + 1\right)},$$

holding fixed $\mathcal{W}_i$ and $\bar{w}_i$ (both of which will also evolve in response to transit in the QSM treatment of amenities).

Derivation of General Equilibrium Parameter Labels

For discrete $T_{ij} \in \{0, 1\}$ with coefficient $\tilde{\beta}$, the following holds exactly:

$$\begin{aligned}
\ln\left(N_{ij}(1)\right) - \ln\left(N_{ij}(0)\right) &= \tilde{\beta} + \ln\left(1 + \frac{N_{ij}(1)}{\bar{N}}(e^{-\tilde{\beta}} - 1)\right) \\
&= \tilde{\beta} + \ln\left(1 - \frac{N_{ij}(1)}{\bar{N}} + e^{-\tilde{\beta}}\frac{N_{ij}(1)}{\bar{N}}\right).
\end{aligned}$$

Asserting $1 - \frac{N_{ij}(1)}{\bar{N}} \approx 0$ and noting that $\ln(x) \approx x - 1$ for x near 1,

$$\tilde{\beta} + \ln\left(1 - \frac{N_{ij}(1)}{\bar{N}} + e^{-\tilde{\beta}}\frac{N_{ij}(1)}{\bar{N}}\right) \approx \tilde{\beta} - \tilde{\beta}\left(\frac{N_{ij}(1)}{\bar{N}} - 1\right) = \tilde{\beta}\left(1 - \frac{N_{ij}(1)}{\bar{N}}\right).$$

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