

Evaluating Urban Transportation with Quantitative Spatial Models

Christopher Severen*

December 13, 2025

Abstract

I describe the use of quantitative spatial models (QSMs) to evaluate the effects of transportation infrastructure with cities. After discussing the motivation for QSMs relative to other economic measurement techniques, I develop a simple QSM and detail the components that enter into the model. Next, I consider identification challenges and practical implementation. Finally, I highlight several shortcomings common in applications of QSMs as well as growth areas where QSMs show promise for future development.

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 and downstream general equilibrium effects. These models represent spatial heterogeneity in a somewhat realistic way and so deliver counterfactuals with rich variation in spatial 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.

*Federal Reserve Bank of Philadelphia, Research Department.

Disclaimer: This paper represents research that is being circulated for discussion purposes. The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. All errors or omissions are the responsibility of the authors.

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 what economic features are modeled, how effects are measured, and identification and calibration strategies for model parameters. 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

This paper has four goals. The first is to broadly survey the various approaches economists have taken to measure the effects of transportation improvements. I try to highlight the benefits and shortcomings of each approach relative to QSMs. There is no approach that strictly dominates another in all settings, as differences in data availability, parameter plausibility, or quasi-experimental variation may rule out certain methods. Careful quantitative and econometric comparisons between methods have yet to be exhaustively studied.

I then describe a simple urban QSM that serves as the core to more complex implementations of QSMs. Third, I discuss how this QSM, and its more complex brethren, can be used to estimate the impacts of transportation projects. I also take the opportunity to discuss practical implementation details, identification, and threats thereto. In particular, I note that one common motivation for using QSMs—that SUTVA is violated and so model-free unbiased treatment effects cannot be recovered—though technically true, impacts the interpretation of estimands rather than the consistency of parameter estimates. Thus, QSMs should ignore parameter identification at the peril of the losing coherence with the research environment.

Lastly, I discuss three shortcomings and two areas of promising growth in the current scholarship using QSMs to evaluate urban transportation.² First, there is often little validation of how transit impacts travel flows. It is common for papers to assume that flows to respond to the intervention under study as they do to long-run changes in travel times, instead of testing whether that is the case. Second, the parameters used in QSMs typically reflect inconsistent temporal or spatial frames. A particular cause of this is the borrowing of parameters across widely varying contexts. Not only might parameters be inconsistent with each other, but they may be inconsistent with particular counterfactuals. Third, there is often little focus on uncertainty in magnitude of effects. Not only is it common to ignore parameter uncertainty, the QSM literature does not always fully consider model uncertainty. This last point is of particular concern; because many QSMs can match observed data perfectly, an unreasonable model can appear to explain the observed spatial distribution of economic activity.

Turning to two growth areas that will benefit from continued research: The first is better incor-

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

2. Because I focus on QSMs, I do not consider very related papers focused on optimal urban transportation policy, such as [Almagro et al. \(2024\)](#) and [Kreindler et al. \(2023\)](#). Such papers do not embed general equilibrium with location choice, and so fall outside of the scope of this survey.

poration of heterogeneity (and its concomitant sorting) into the QSM paradigm. Better reflecting heterogeneity in QSMs allows these models to more sharply engage with the rich social and economic tapestries present in cities. However, heterogeneity suggests sorting, and it can be difficult to interpret the effects of transportation solely through gross commuting flows or changes in prices when sorting plays a meaningful role. The second is the use of QSMs to isolate non-commuting effects of transportation infrastructure within cities. Given that infrastructure projects can transform physical environments, their effects extend beyond merely changing the flows of travelers.

So, what is the researcher who seeks to evaluate urban transportation innovations to do? QSMs are a powerful and useful tool, and like any tool, it matters *how* it is used. My hope is to increase the transparency of both the benefits and shortcomings of QSMs for the study of urban transportation. My intent is to help bridge the policy evaluation literature as practiced in applied microeconomics with more applied theory approach of QSMs. In that sense, this review should complement other recent reviews that contemplate transportation evaluation with QSMs.³ As such, an essential reference is [Redding and Turner \(2015\)](#), who combine exposition of a QSM framework to study transportation costs with discussion of careful causal identification methods. While opinionated, I do not intend for these views to dictate how the literature will proceed. Rather, I hope researchers, referees, and practitioners find this article useful to collectively continue the process of developing and improving the credibility of QSM applications.

2 Motivations for and Alternatives to QSMs

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. QSMs are the newest method, complementing these existing approaches. Collectively, these methods enable researchers to model a wide variety of urban phenomena in response to transportation interventions.

Hedonic analysis of transportation measures the effects of exposure or proximity to the transportation system on property values. The intellectual tradition for this approach is based on the capitalization of amenities, such as those provided by transportation access, into property values in equilibrium. *Ceteris paribus*, properties with greater transportation access will be priced higher than those with less, and this difference 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; it is difficult to separate the benefits

3. [Redding \(2025\)](#) applies the model in [Ahlfeldt et al. \(2015\)](#) to study hypothetical transportation improvements and compares how successful a market-access only approach is to relative to a full QSM. [Donaldson \(2025\)](#) centers his review around a sufficient statistics approach framed by the welfare results of [Hulten \(1978\)](#). Although much of [Donaldson \(2025\)](#) discusses this theoretical framework, there are also enlightening sections on measurements and causal identification.

4. The capitalization of transportation into housing prices has been studied since at least [Spengler \(1930\)](#).

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](#)).⁵

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. [Barwick et al. \(2021\)](#), [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 typically address this by incorporating workplace and therefore commuting. However, when these models do not ignore work location, workplace is treated as fixed. As such, sorting models cannot quantify how transportation may shift the spatial distribution of production and consumption.

Although it often shares discrete choice methodology 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 is on understand agents' mode choice problem, along with some attention to trip generation and routing.⁶ As such, the travel demand literature typically recovers estimates reflecting the marginal disutility of travel time or the marginal value of time. It is less well-equipped to 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 modeling tradition means that it is often deployed as a nest within equilibrium sorting models and within QSMs.

2.1 Motivations for QSMs

Hedonic valuation, equilibrium sorting models, and travel demand analysis are all intellectually adjacent to modern urban QSMs, but typically have rather different goals. QSMs are well positioned to model how changes in transportation shift the spatial distribution of economic activity within a city, inclusive of production (and consumption). While QSMs are often motivated as overcoming the limitations of other approaches, that is somewhat inaccurate, as QSMs are themselves limited in the margins that they can address. Moreover, well executed QSMs are often quite

5. Under some assumptions, these causal estimates can provide information about willingness to pay for and the welfare effects of transit ([Banzhaf 2021](#)). Also 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 \(2007\)](#).

data and parameter hungry, a factor that can limit feasibility. Each approach has value to add, and they should be seen as complements rather than substitutes.

The motivation for using QSMs to evaluate urban transportation typically falls into one of three categories. The first is that in an urban economy, residential and production location choices are determined in spatial equilibrium, which interconnect all places within a city. Through such a lens, there is no distinction between locations affected by changes in transportation and unaffected locations. As such, there are no clean control locations, a violation of the Stable Unit Treatment Value Assumption (SUTVA) (e.g., [Angrist, Imbens, and Rubin 1996](#)). When SUTVA is violated, average treatment effects cannot be consistently estimated from a standard regression model.

A second motivation is welfare analysis. As long as the QSM provides a reasonable first- or second-order approximation of the relevant economic environment, it naturally provides 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 2024](#); [Tsivanidis 2025](#)).

The final common motivation is that QSMs can incorporate and reflect a variety of mechanisms through which transportation infrastructure could shift 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, [Tsivanidis \(2025\)](#) considers counterfactuals that limit externalities, restrict heterogeneity, incorporate congestion, or allow for migration. The use of QSMs for policy evaluation also allows the potential for assessing the complementarity or substitutability of different channels.

Although these are the common motivations for the use of QSMs, there are a few other reasons to employ QSMs in urban settings. First, market access terms may be interesting in and off themselves as objects of measurement, in the tradition of [Harris \(1954\)](#). Relatedly, such an approach can be further developed so as to provide a systematic approach to identification, as [Baum-Snow and Han \(2024\)](#) do to develop local estimates of housing supply elasticities. Finally, QSMs can also be viewed as part of 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](#)).

3 A Simple 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 diverges by assuming that land use is exogenous and that there are no agglomeration forces in firm

productivity or residential amenities. Labor and housing markets are otherwise free to respond according to market forces. I write the model to accommodate a generic notion of “travel costs” between locations; this can nest sub-models incorporating mode or route choice.⁷

3.1 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 effects indirect utility.⁸ The indirect utility of household o residing in residential location i and working j is:

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

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 v_{ijo} is household o 's idiosyncratic preference for location pair ij .⁹ The term δ_{ij} measures the travel cost between i and j . Written as such, travel costs nest several implementations that may themselves feature interesting economic problems, aid identification, or both.¹⁰

The key tractability assumption in QSMs is typically that the v_{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 are 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 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 such, the value of ϵ effectively determines the magnitude of the

7. The baseline model is reasonably well targeted for studying the short- to medium-run effects of urban transportation innovations in large cities with binding land use regulations. The omission of spillovers means the baseline model is best interpreted as providing a first-order approximation of the effects of transportation innovations that are relatively small in comparison to the city they are in. Although that (unfortunately) means the baseline model is well suited to evaluating most mass transit projects in the United States, it does limit its usefulness for large interventions or to study long-run effects.

8. This model assumes Cobb-Douglas utility in the consumption of a numeraire good and housing. Richer specifications may reflect, e.g., non-homothetic preferences ([Tsivanidis 2025](#)), household bargaining ([Velásquez 2023](#)), or the consumption other goods ([Miyauchi, Nakajima, and Redding 2021](#)).

9. 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.

10. It is common to instead write travel costs as δ_{ij}^{-1} ; I differ to maintain consistency with the several interpretations of travel costs in [Section 4](#).

mapping from changes in prices and travel costs 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 v_{ijo} is $F_{ij}(v) = \exp(B_i E_j D_{ij} v^{-\epsilon})$. 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.¹¹ Although Λ_{ij} and its components are typically given names that evoke a certain interpretation (i.e., amenity), they function as (model) residuals. As such, literal interpretation of these variable labels warrants caution.

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

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

in which \bar{N} represent the total residents in a city and 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 as such, recalls the denominator of a multinomial logit estimator. In fact, similar to the log-sum term for multinomial logit, taking expectations across all location pairs generates a welfare term:

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

where $\gamma_\epsilon = \Gamma(\frac{\epsilon-1}{\epsilon})$ and Γ is the gamma function.¹² 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, v_{ijo} , will be. Welfare, \bar{V} , is an index of 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 consistent with the indirect utility in this model is $(1 - \zeta)W_j/Q_i$. Total housing demand in i combines these two terms to sum demand from households who work in difference places: $(1 - \zeta)\bar{N} \sum_s \pi_{is} W_s/Q_i$. Total labor supply to j is $N_{Wj} \equiv \bar{N} \sum_r \pi_{rj}$.

11. 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 by the shape parameter has little substantive effect.

12. 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 $U_{ij} = \ln \Lambda_{ij} + \epsilon \ln W_j - \epsilon(1 - \zeta) \ln Q_i - \epsilon \ln \delta_{ij} + e_{ijo}$, where e_{ijo} is distributed Type 1 extreme value. This generates choice probabilities $\exp(U_{ij}) / (\sum_{r,s} \exp(U_{rs}))$, which, when evaluated, are identical to Equation (1).

3.2 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 that is multiplicatively separable in productivity A_j . Thus, aggregating across firms gives a local production function:

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

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,

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

Measure-zero developers build housing using Cobb-Douglas technology in land and materials, with productivity that varies by location. Land 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:

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

3.3 Equilibrium and Inversion

The model expressed in Equations (1)–(4), along with market clearing conditions in labor markets ($N_{Wj} \equiv \bar{N} \sum_r \pi_{rj}$) and housing markets ($H_i = (1 - \zeta) \bar{N} \sum_s \pi_{is} W_s / Q_i$) defines a unique equilibrium under reasonably mild parametric conditions.¹³ For convenience, the set of terms A_i , C_i , Λ_{ij} , and δ_{ij} are often called fundamentals, but are also model (structural) residuals. The existence and uniqueness of the equilibrium means that means any non-pathological combination of fundamentals maps to a unique matrix of population (with elements π_{ij}) and vectors of prices (with elements W_i and Q_i).

A sometimes 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

13. See [Severen \(2023\)](#) for details.

on wages, housing prices, commuting flows, and travel costs. 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 travel costs, deliver four vectors and one matrix of fundamentals.¹⁴

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 directly conformable to the their model, and so cannot separately residuals A_i and E_i (they 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, it is difficult to identify more dimensions of fundamentals (i.e., geographic richness) than there are vectors of observed data.

3.4 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

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

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

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

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

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

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

Note that ϵ and the denominator of Equation (6) together can then be used to calculate welfare, as

¹⁴ 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.

per Equation (5).

This model is of a closed city: the population is fixed and agents can only choose locations within the city. This has the important implication that welfare may change in response to transportation infrastructure. In contrast, a fully open city faces a perfectly elastic supply of population, and so the response to changes in travel costs is to alter the size of the city without impacting welfare. An intermediate assumption is possible, nesting a migration decision (often defined in terms of a separate idiosyncratic extreme value term) between the expected value of city residence expressed in [Equation 2](#) and a rest-of-country option.

3.5 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 quantity of people that travel 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 between transit and changes in automobile congestion by regressing changes in travel times on the share of a 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.

Another motivation for endogenizing travel time is to study the supply of transportation. [Bordieu \(2024\)](#) extends the [Allen and Arkolakis \(2022\)](#) framework by allowing fragmented governments within a city to decide how much roadway to provide, this 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 \(2023\)](#) considers the incentives to provide high quality travel services of associations of private transit providers. Indeed, these two papers demonstrate that QSMs are useful to learn about the supply of transportation as much as about the demand for transportation.

4 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.

4.1 Measuring Commuting Effects

Taking logs and rearranging Equation (1) yields:

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

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 interpreting $d_{ij} \equiv \ln(D_{ij})$ as a residual, this becomes

$$\ln(N_{ij}) = g_0 + \theta_i + \omega_j + \epsilon \ln \delta_{ij} + d_{ij}. \quad (9)$$

The commuting model thus delivers a tractable empirical estimating equation that depends on travel costs (δ_{ij}), fixed effects (which may subsume the constant g_0), and an error term.

Measuring how transportation impacts 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 sub-model of mode choice or to directly a measure of exposure, proximity or treatment. Each approach has merits, which I detail below. To unify notation, define

$$\delta_{ij} = \begin{cases} e^{-\kappa \tau_{ij}} & \text{for travel time with a single mode} \\ \sum_m e^{u_m(-\kappa \tau_{ijm})} & \text{for travel times with multiple modes} \\ e^{\beta T_{ij}} & \text{for direct measure of treatment (exposure) to transit,} \end{cases}$$

where τ_{ij} is the travel time from i to j , κ is the marginal utility of travel time, τ_{ijm} is the mode- m specific travel time from i to j , and T_{ij} is a direct measure of exposure or treatment.

4.1.1 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 $\delta_{ij} = \exp(\kappa\tau_{ij})$ into Equation (9) yields:

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

Travel times directly enter Equation (10), and under conditional exogeneity, this equation recovers consistent estimates of the compound parameter $\epsilon\kappa$.¹⁵ However, there is insufficient variation in Equation (10) to separately identify these two parameters. 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 a few additional challenges. First, researchers faces several degrees of freedom in the sampling process. They must determine whether to use a single point (typically the centroid) per 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 $\epsilon\kappa$.

4.1.2 From Travel Times with Multiple Modes

Alternatively, a mode choice sub-model can be used to capture travel costs and 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

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

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.

16. Some care should be taken in this stage; e.g., some centroids may lie in inaccessible locations. Special care should be paid at calculating the time from i to j ; 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.

Substituting this expression into Equation (9) gives:

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

This model is similar to Equation (10), but has one key difference. The marginal disutility of travel time, κ , is estimated using variation travel times across modes. This source of variation conditions on ij , but is otherwise independent from the selection of origin and destination. Thus, estimates of ϵ can be obtained from directly from Equation (11) (under conditional exogeneity).

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 model could be even richer, such as featuring nested mode decisions (as in [Tsivanidis 2025](#)) or routing decisions (as in [Allen and Arkolakis 2022](#)).¹⁷

4.1.3 Directly from Treatment

Alternatively, $\ln(\delta_{ij})$ can directly measure exposure to infrastructure. For example, let $\ln(\delta_{ij}) = \tilde{\beta}g(d_s(i), d_s(j)) = \tilde{\beta}T_{ij}$ 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).¹⁸ Under this assumption, substituting into Equation (9) gives:

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

As in the case of the single mode model, Equation (12) only recovers the compound parameter $\epsilon \tilde{\beta}$. However, a benefit of this model is that it may be possible to interpret $\beta \equiv -\epsilon \tilde{\beta}$ as a treatment effect (or as proportional to the treatment effect; see Section 5.1). Again, a sufficient requirement for identification is conditional exogeneity.

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 6](#).

17. [Allen, Fuchs, and Wong \(2025\)](#) build on [Fuchs and Wong \(2024\)](#) and develop an alternative way of incorporating multi-modal travel.

18. 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.

4.2 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:

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

where constant terms have been omitted.¹⁹ 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:

$$\mathbf{Y}_i = \boldsymbol{\lambda} T_i + \mathbf{u}_i, \tag{13}$$

where $\mathbf{Y}_i = \{\ln(A_i), \ln(B_i), \ln(C_i), \ln(E_i)\}$ are the fundamentals recovered above, $\boldsymbol{\lambda} = \{\lambda^A, \lambda^B, \lambda^C, \lambda^E\}$ estimate the impacts of T_i , and $\mathbf{u}_i = \{a_i, b_i, c_i, e_i\}$ are residuals of the auxiliary regression. 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 such, this representation is conformable to agglomerative spillover terms, such as those in [Ahlfeldt et al. \(2015\)](#).

5 Interpretation, Identification, and Practical Details

I next address common issues that face researchers trying to implement or understand the use of QSMs when studying urban transportation.

¹⁹ Note that the land use terms are present in this system, even though they are taken as exogenous in the baseline model.

5.1 Interpreting Parameters in QSMs

A key motivation for evaluating urban transportation with QSMs are the 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, rendering parameter estimates based on quasi-experimental techniques unidentified. These concerns certainly have the potential to complicate identification, but there is a lack of clarity about the circumstances under which each concern is valid.²⁰

5.1.1 SUTVA Violations and Parameter Labels in Partial Equilibrium

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, the parameters $\{\alpha, \epsilon, \kappa, \psi, \zeta\}$ do not represent elasticities or semi-elasticities and $\beta = \epsilon\tilde{\beta}$ 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 Equation (10) (which maintains the assumption of extreme-value idiosyncratic preferences). Although $\epsilon\kappa$ appears to represent the semi-elasticity of commuting flows with respect to travel times, straightforward derivation reveals that, in partial equilibrium,

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

Similarly, consider Equation (12) with a discrete treatment $T_{ij} \in \{0, 1\}$. Let $N_{ij}(T_{ij})$ be the counterfactual value N_{ij} as a function of treatment T_{ij} , and let $\beta \equiv \epsilon\tilde{\beta}$. Then, in partial equilibrium,

$$\ln(N_{ij}(1)) - \ln(N_{ij}(0)) = \beta + \ln\left(1 + \frac{N_{ij}(1)}{\bar{N}}(e^{-\beta} - 1)\right) \approx \beta \left(1 - \frac{N_{ij}(1)}{\bar{N}}\right).$$

In both of these instances, the (semi-)elasticity or treatment effect is simply scaled by the fraction of the population that chooses each location. True partial equilibrium treatment effects and elasticities can be calculated by taken averages across ij . However, because π_{ij} is often quite small, the true effects or elasticities will typically be close to the parameter values themselves. Given this, the shorthand practice of referring to these parameters as elasticities or treatment effects is

20. For example, [Diamond and Serrato \(2025\)](#) notes 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.

not unreasonable, as long as careful analysis preserves the distinction.

5.1.2 Moving from Partial to General Equilibrium

The above distinction between parameters and treatments or elasticities is mainly semantic in partial equilibrium, but becomes more substantive when general equilibrium forces are allowed or suspected to operate. 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 parameter 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.

5.2 Identifying Commuting Effects and Practical Estimation Details

I now touch on factors that impact the identification and estimation of the gravity (commuting) equation, as these tend to be somewhat distinct from identification of other parameters (which typically reflect more common identification in labor, urban, and housing economics). The gravity equation hosts 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 be 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.

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):

$$\ln(N_{ijt}) = g_{0t} + \theta_{it} + \omega_{jt} + \mu_{ij} + \epsilon \ln \delta_{ijt} + d_{ijt}. \quad (14)$$

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.²¹

This enables using difference-in-difference or staggered-adoption designs to identify transportation effects, as in [Gaduh, Gračner, and Rothenberg \(2022\)](#). The credibility of these approaches depend 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 outside information to refine identification, 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 are 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 $j \neq j'$ are 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 be or have been particularly likely to have been treated, yet were not (or were not yet) treated. Several papers adopt this approach. [Tsivanidis \(2025\)](#) 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 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 are the use of inconsequential units designs, wherein treatment can be instrument by whether a route lies along the lines connecting two important locations. [Tsivanidis \(2025\)](#) 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](#)).

Several papers propose using historical urban transportation networks as instruments, as opposed to developing a refined control group. The validity of exclusion restrictions based on a historical network effectively limits any independent role of persistence in urban form. For example, [Brooks and Lutz \(2019\)](#) find that locations historically served by tramways are still 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 exclusion restriction is violated.

21. 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).

5.2.1 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:

$$\mathbb{E}[N_{ij}] = \exp(\theta_i + \omega_j + \epsilon \ln \delta_{ij}), \quad (15)$$

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.²² 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.²³

Second, there may be substantial granularity if units are at a small level of disaggregation, with N_{ij} predominately 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 2025).

Sotelo (2019) notes another, subtle issue. There are alternative ways to write Equation (9) 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.

6 Shortcomings and Opportunities

I next summarize three common shortcomings in how QSMs are implemented when studying transportation. These critiques tend to be interrelated, and although they are targeted primarily at transportation settings, they may apply more generally to the implementation of QSMs in other contexts. I then turn to two areas of exciting research growth that retain opportunities for continued discovery.

22. Bellégo, Benatia, and Pape (2022) propose another solution to the so-called “log of zero” problem (Silva and Terreyro 2006).

23. 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.

6.1 Validating Effects on Flows

Researchers do not always validate the causal link from transportation infrastructure to commuting flows. Instead, as discussed in Section 4.1, 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 any behavioral or unmodeled changes in travel behavior. 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 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 in the way that people respond to changes in travel time is invariant the temporal scale under study. In fact, this elasticity (or semi-elasticity) must always be in reference some time frame over which reaction can occur. If a commuter's travel time increases by 30 or 60 minutes, they are unlikely to respond by changing their residence and workplaces the next day. In fact, such responses can take a rather long time to play out.

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 as a causal average treatment effect estimated by regressing flows on (changes in) proximity to treatment. This is the approach of [Gaduh, Gračner, and Rothenberg \(2022\)](#), who find a minimal direct effect of bus rapid transit on commuting flows in Jakarta. [Severen \(2023\)](#) also follows this direct approach, but finds a substantial direct effect of subway and light rail on commuting flows in Los Angeles. [Tyndall \(2025\)](#) directly estimates the effects of ferry connections in New York City using a panel gravity model.

6.2 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. As such, they may reflect behaviors at inconsistent temporal or spatial scales.²⁴ Economists have long been familiar with the idea that

24. 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

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 the shape parameter governing the dispersion of idiosyncratic preferences over residential locations is estimated from tract-level variation in Berlin, it is unclear that it is also reasonable to use that parameter to study county-level residence choice in the United States.²⁵

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 annual or decadal 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 paper exacerbates 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.²⁶ This can be both a feature and lead to challenges. For example, in the model presented in [Section 3](#), 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 in interpretation suggests many ways to calibrate or estimate the parameter. However, if these different interpretations suggest different parameter values, it may not be clear how best to proceed.

this brew is provide the protagonist with false visions and give a dangerous and unfounded sense of security of the future. This false information guides him to making rash decisions and committing rather unreasonable actions.

25. As such, this is related to the modifiable areal unit problem (MAUP) in spatial statistics.

26. 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](#)).

6.3 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 may suppress the often significant uncertainty over parameter values. In models with many parameters, correlation in the uncertainty over these parameters may lead to substantial differences in model performance. Ideally, sensitivity analysis should span the plausible subset of vector space covered by these parameters, though in practice this is unlikely feasible.²⁷ [Cocci and Plagborg-Møller \(2025\)](#) offer a conservative method to incorporate parameter uncertainty under worst-case assumptions about correlation across parameters. 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.

Moreover, there may be substantial model uncertainty. Although this is not unique to QSMs, the wide menu of choices that can be selected when constructing a QSM suggest that the researcher has a substantial degree of freedom. This is an embarrassment of riches, but highlights that the QSM enterprise would be well serve 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). This suggests that, 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 generates the same conclusion, then this conclusion is tautological with respect the model and thus unhelpful for distinguishing various narratives for how the world works. A second approach is 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.²⁸

27. Appropriately addressing uncertainty in dyadic models is not trivial, and applications of available methods (e.g., [Graham 2020](#)) not widespread.

28. The set of quantitative tools available to validate structural models growing (e.g., [Andrews, Gentzkow, and](#)

6.4 Incorporating Heterogeneity (and Concomitant Sorting)

Standard QSM implementations feature agents that are identical (up to an idiosyncratic preference shock). This model can be extended by have multiple discrete types of agents that are distinguished by a pre-determined 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, [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 \(2025\)](#) 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.

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.

A particular challenge emerges as a logical consequence of *ex ante* heterogeneity: sorting. People may move to take advantage of transportation infrastructure. When this on the basis of observable differences, QSMs accompanied by sufficiently detailed data are well positioned to analyze effects. However, when sorting takes place on the basis of unobservable heterogeneity, it is more challenging to address. Indeed, in the limit, where every agent is *ex ante* different, fully incorporating sorting is impossible without panel data. And panel data that follow agents at spatial granularity sufficient for within city analysis are rare. However, [Warnes \(2024\)](#) obtains such data for Buenos Aires, and is thus able to model how households respond to the introduction of bus rapid transit while accounting for moving frictions. As a warning about the importance of sorting, [Balboni et al. \(2025\)](#) show that controlling linearly for only observable demographic factors does relatively little to address sorting.

[Shapiro 2020; Adão, Costinot, and Donaldson 2025](#).

6.5 Non-Commuting Effects of Transportation

With the possible exception of congestion, the primary response considered in studies of urban transportation is commuting behavior. This is typically due to the availability of data, but also reflects the fact that visiting a work location daily lends that location particular import. However, there are many other margins that urban transportation can influence. The literature considering these alternative margins is rapidly expanding, to the great benefit of researchers and policymakers.²⁹

In addition to providing access to work, transportation also provides access to consumption opportunities. [Miyauchi, Nakajima, and Redding \(2021\)](#) 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.

Not only does consumption access appear to play a substantial role, so does variation in destinations for members within a household. [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 parents' trade offs between work access for themselves and schools for their children.

Several studies incorporate the effects of highway infrastructure on non-commuting fundamentals, and in particular, on residential amenities $\{B_i\}$. [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](#); [Weiwei 2025](#)). Given the substantial impact that infrastructure can have on the built environment, this type of research seems particularly important for understanding urban dynamics.

The sorting and segregation studied in [Bagagli \(2025\)](#) and [Weiwei \(2025\)](#) represents 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 \(2025\)](#) 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. Despite the explanatory success of these approaches, there is still a sense in which these endogenous residential amenities may stand in for more precise local characteristics,

29. This is not to understate the important role of commuting nor the ability of QSMs to offer new and interesting insights about commuting. For example, [Delventhal, Kwon, and Parkhomenko \(2022\)](#) use a QSM framework to study how work-from-home shocks change the within-city distribution of economic activity.

such as characteristics of the housing stock, local consumption options, or perceived safety. An intriguing avenue of study is 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.³⁰

There has been somewhat less of a focus in studying the direct local productivity effects of transportation (beyond agglomeration).³¹ Many QSM models 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.

Although transportation infrastructure does not typically directly impact the efficiency of housing or real estate supply, land use statutes are often bundled with transportation or interact with the location of transportation. Integrating analysis of transportation and housing supply is therefore of particular interest, especially if there are substantial complementarities between these policy levers. To this end, [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 finding 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.

7 Conclusion

QSMs offer an extensive paradigm to study how transportation infrastructure drives the evolution of urban economic geography. Despite this, it is often unclear what best practices are 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

30. [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 also a warning that amenity fundamentals reflect other variation that may, or may not, accord with beliefs about what amenities represent.

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

and conscientious implementation that reflects best practices. However, as 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 make a modest attempt at clarifying current practices that are consistent with high-confidence estimates. I contrast this with other practices that may inject uncertainty in interpreting model results. And throughout, I try include intuition for how QSMs rationalize the data we feed them.

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 are making these models broadly accessible to researchers. We should endeavor to ensure that these models be as transparent as possible, and validate their use critically and carefully.

References

- Adão, Rodrigo, Arnaud Costinot, and Dave Donaldson. 2025. "Putting Quantitative Models to the Test: An Application to the US-China Trade War." *The Quarterly Journal of Economics* 140 (2): 1471–1524.
- Ahlfeldt, Gabriel M, Stephen J Redding, Daniel M Sturm, and Nikolaus Wolf. 2015. "The economics of density: Evidence from the Berlin Wall." *Econometrica* 83 (6): 2127–2189.
- Akbar, Protttoy, Victor Couture, Gilles Duranton, and Adam Storeygard. 2023. "Mobility and congestion in urban India." *American Economic Review* 113 (4): 1083–1111.
- Allen, Treb, and Costas Arkolakis. 2022. "The welfare effects of transportation infrastructure improvements." *The Review of Economic Studies* 89 (6): 2911–2957.
- . 2025. "Quantitative Regional Economics." In *Handbook of Regional and Urban Economics*, edited by Dave Donaldson and Stephen J. Redding, 6:1–72. Handbook of Regional and Urban Economics 1. Elsevier.
- Allen, Treb, and Dave Donaldson. 2020. *Persistence and path dependence in the spatial economy*. Technical report. National Bureau of Economic Research.
- Allen, Treb, Simon Fuchs, and Woan Foong Wong. 2025. "Evaluating Transportation Improvements Quantitatively: A Primer."
- Almagro, Milena, Felipe Barbieri, Juan Camilo Castillo, Nathaniel G Hickok, and Tobias Salz. 2024. *Optimal Urban Transportation Policy: Evidence from Chicago*. Technical report. National Bureau of Economic Research.
- Almagro, Milena, and Tomás Domínguez-Iino. 2025. "Location sorting and endogenous amenities: Evidence from Amsterdam." *Econometrica* 93 (3): 1031–1071.
- Alves, Guillermo, William H Burton, and Sebastian Fleitas. 2025. "Difference-in-Differences When Units Are Substitutes: Evidence from Place-Based Policies."
- Anagol, Santosh, Fernando Vendramel Ferreira, and Jonah M Rexer. 2021. *Estimating the economic value of zoning reform*. Technical report. National Bureau of Economic Research.
- Anderson, Michael L. 2014. "Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion." *American Economic Review* 104 (9): 2763–2796.
- Andrews, Isaiah, Matthew Gentzkow, and Jesse M Shapiro. 2020. "Transparency in structural research." *Journal of Business & Economic Statistics* 38 (4): 711–722.
- Ang, Amanda, Daniel Angel, and Andrii Parkhomenko. 2024. "Amenities in Quantitative Spatial Models."
- Angrist, Joshua D, Guido W Imbens, and Donald B Rubin. 1996. "Identification of causal effects using instrumental variables." *Journal of the American Statistical Association* 91 (434): 444–455.
- Bagagli, Sara. 2025. "The (Express) Way to Segregation: Evidence from Chicago." *Job Market Paper*.

- Balboni, Clare, Gharad Bryan, Melanie Morten, Caylee O'Connor, and Bilal Siddiqi. 2025. *Impacts of Infrastructure: People versus Place*. Technical report. working paper.
- Banzhaf, H Spencer. 2021. "Difference-in-Differences Hedonics." *Journal of Political Economy* 129 (8): 2385–2414.
- Barjamovic, Gojko, Thomas Chaney, Kerem Coşar, and Ali Hortaçsu. 2019. "Trade, merchants, and the lost cities of the bronze age." *The Quarterly Journal of Economics* 134 (3): 1455–1503.
- Barwick, Panle Jia, Shanjun Li, Andrew R Waxman, Jing Wu, and Tianli Xia. 2021. *Efficiency and equity impacts of urban transportation policies with equilibrium sorting*. Technical report. National Bureau of Economic Research.
- Baum-Snow, Nathaniel, and Lu Han. 2024. "The microgeography of housing supply." *Journal of Political Economy* 132 (6): 1897–1946.
- Baum-Snow, Nathaniel, and Matthew E Kahn. 2000. "The effects of new public projects to expand urban rail transit." *Journal of Public Economics* 77 (2): 241–263.
- Bellégo, Christophe, David Benatia, and Louis Pape. 2022. "Dealing with logs and zeros in regression models." *arXiv preprint arXiv:2203.11820*.
- Billings, Stephen B. 2011. "Estimating the value of a new transit option." *Regional Science and Urban Economics* 41 (6): 525–536.
- Bordeu, Olivia. 2024. "Commuting Infrastructure in Fragmented Cities." PhD diss., The University of Chicago.
- Brinkman, Jeffrey, and Jeffrey Lin. 2024. "Freeway revolts! The quality of life effects of highways." *Review of Economics and Statistics*, 1–17.
- Brooks, Leah, and Byron Lutz. 2019. "Vestiges of transit: Urban persistence at a microscale." *Review of Economics and Statistics* 101 (3): 385–399.
- Chang, Konhee. 2024. "Diversifying the suburbs: Rental supply and spatial inequality." *Available at SSRN 5011422*.
- Chen, Liming, Rana Hasan, Yi Jiang, and Andrii Parkhomenko. 2024. "Faster, taller, better: Transit improvements and land use policies." *Journal of Development Economics* 171:103322.
- Chernoff, Alex, and Andrea N Craig. 2022. "Distributional and housing price effects from public transit investment: Evidence from Vancouver." *International Economic Review* 63 (1): 475–509.
- Cocci, Matthew D, and Mikkel Plagborg-Møller. 2025. "Standard errors for calibrated parameters." *Review of Economic Studies* 92 (5): 2952–2978.
- Conwell, Lucas. 2023. "Subways or minibuses? Privatized provision of public transit."
- Delventhal, Matthew J, Eunjee Kwon, and Andrii Parkhomenko. 2022. "JUE Insight: How do cities change when we work from home?" *Journal of Urban Economics* 127:103331.
- Diamond, Rebecca, and Juan Carlos Suárez Serrato. 2025. "Spatial Sorting and Inequality." In *Handbook of Regional and Urban Economics*, vol. 6. North Holland.

- Dingel, Jonathan I, and Felix Tintelnot. 2025. *Spatial economics for granular settings*. Technical report. National Bureau of Economic Research.
- Donaldson, Dave. 2025. "Transport infrastructure and policy evaluation." In *Handbook of Regional and Urban Economics*, 6:287–352. North Holland.
- Eastman, P. D. 1961. *Go, Dog. Go!* New York: Beginner Books.
- Fogel, Robert William. 1964. *Railroads and American economic growth*. Baltimore: Johns Hopkins Press.
- Fuchs, Simon, and Woan Foong Wong. 2024. "Multimodal transport networks."
- Gaduh, Arya, Tadeja Gračner, and Alexander D Rothenberg. 2022. "Life in the slow lane: Unintended consequences of public transit in Jakarta." *Journal of Urban Economics* 128:103411.
- Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics* 225 (2): 254–277.
- Graham, Bryan S. 2020. "Dyadic regression." *The econometric analysis of network data*, 23–40.
- Gupta, Arpit, Stijn Van Nieuwerburgh, and Constantine Kontokosta. 2022. "Take the Q train: Value capture of public infrastructure projects." *Journal of Urban Economics* 129:103422.
- Harris, Chauncy D. 1954. "The, Market as a Factor in the Localization of Industry in the United States." *Annals of the association of American geographers* 44 (4): 315–348.
- Heblich, Stephan, Stephen J Redding, and Daniel M Sturm. 2020. "The making of the modern metropolis: evidence from London." *The Quarterly Journal of Economics* 135 (4): 2059–2133.
- Herzog, Ian. 2024. "The city-wide effects of tolling downtown drivers: Evidence from londonâs congestion charge." *Journal of Urban Economics* 144:103714.
- Hu, Wenhao, and Lili Wang. 2025. "Building the Metropolis: Subway Expansion, Land Use Regulation, and Welfare." *Journal of Housing Economics*, 102102.
- Hulten, Charles R. 1978. "Growth accounting with intermediate inputs." *The Review of Economic Studies* 45 (3): 511–518.
- Hwang, Yooseon. 2024. "The Welfare Effects of Congestion Pricing: Evidence From High-Occupancy Toll Lanes." Available at SSRN 5038317.
- Khanna, Gaurav, Anant Nyshadham, Daniel Ramos-Menchelli, Jorge Andrés Tamayo, and Audrey Tiew. 2023. *Spatial mobility, economic opportunity, and crime*. Harvard Business School.
- Koh, Yumi, Jing Li, and Jianhuan Xu. 2025. "Subway, collaborative matching, and innovation." *Review of Economics and Statistics* 107 (2): 476–493.
- Kreindler, Gabriel, Arya Gaduh, Tilman Graff, Rema Hanna, and Benjamin A Olken. 2023. *Optimal Public Transportation Networks: Evidence from the World's Largest Bus Rapid Transit System in Jakarta*. Technical report. National Bureau of Economic Research.
- Kreindler, Gabriel E, and Yuhei Miyauchi. 2023. "Measuring commuting and economic activity inside cities with cell phone records." *Review of Economics and Statistics* 105 (4): 899–909.

- Le Barbanchon, Thomas, Roland Rathelot, and Alexandra Roulet. 2021. "Gender differences in job search: Trading off commute against wage." *The Quarterly Journal of Economics* 136 (1): 381–426.
- Lee, Kwok Hao, and Brandon Joel Tan. 2024. "Urban transit infrastructure and inequality." *Review of Economics and Statistics*, 1–46.
- Liu, Sitian, and Yichen Su. 2024. "The geography of jobs and the gender wage gap." *Review of Economics and Statistics* 106 (3): 872–881.
- McFadden, Daniel. 1974. "The Measurement of Urban Travel Demand." *Journal of Public Economics* 3 (4): 303–328.
- Milgrom, Paul, and John Roberts. 1996. "The LeChatelier Principle." *American Economic Review*, 173–179.
- Miyauchi, Yuhei, Kentaro Nakajima, and Stephen J Redding. 2021. *The economics of spatial mobility: Theory and evidence using smartphone data*. Technical report. National Bureau of Economic Research.
- Monte, Ferdinando, Stephen J Redding, and Esteban Rossi-Hansberg. 2018. "Commuting, Migration, and Local Employment Elasticities." *American Economic Review* 108 (12): 3855–90.
- Mulalic, Ismir, and Jan Rouwendal. 2020. "Does improving public transport decrease car ownership? Evidence from a residential sorting model for the Copenhagen metropolitan area." *Regional Science and Urban Economics* 83:103543.
- Nagengast, Arne J, and Yoto V Yotov. 2025. "Staggered difference-in-differences in gravity settings: Revisiting the effects of trade agreements." *American Economic Journal: Applied Economics* 17 (1): 271–296.
- Pérez, Jorge, Felipe Vial, and Román Zárate. 2022. "Urban transit infrastructure: Spatial mismatch and labor market power."
- Piazzesi, Monika, Martin Schneider, and Johannes Stroebel. 2020. "Segmented housing search." *American Economic Review* 110 (3): 720–759.
- Pietrabissa, Giorgio. 2023. "School access and city structure." *Unpublished manuscript*.
- Redding, Stephen J. 2025. *Evaluating transport improvements in spatial equilibrium*. Technical report. National Bureau of Economic Research.
- Redding, Stephen J, and Matthew A Turner. 2015. "Transportation costs and the spatial organization of economic activity," 5th ed., edited by Gilles Duranton, J. Vernon Henderson, and William C. Strange, 1339–1398. *Handbook of Regional and Urban Economics*. Elsevier.
- Redding, Stephen J, and David E Weinstein. 2019. "Aggregation and the gravity equation." In *AEA Papers and Proceedings*, 109:450–455. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.
- Samuelson, P.A. 1947. *Foundations of Economic Analysis*. Cambridge, MA: Harvard University Press.

- Severen, Christopher. 2023. "Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification." *Review of Economics and Statistics* 105 (5): 1073–1091.
- Shoup, Donald C. 2003. "Truth in Transportation Planning." *Journal of Transportation and Statistics* 6 (1): 1–12.
- Silva, JMC Santos, and Silvana Tenreyro. 2006. "The log of gravity." *Review of Economics and Statistics* 88 (4): 641–658.
- Small, Kenneth, and Erik Verhoef. 2007. *The Economics of Urban Transportation*. New York, NY: Routledge.
- Sotelo, Sebastian. 2019. "Practical aspects of implementing the multinomial pml estimator." *Ann Arbor: University of Michigan, mimeo*.
- Spengler, Edwin H. 1930. *Land Values in New York in Relation to Transit Facilities*. New York City, NY: Columbia University Press.
- Train, Kenneth E. 2009. *Discrete choice methods with simulation*. Cambridge University Press.
- Tsivanidis, Nick. 2025. "Evaluating the Impact of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio."
- Tyndall, Justin. 2021. "The local labour market effects of light rail transit." *Journal of Urban Economics* 124:103350.
- . 2025. "Estimating commuter benefits of a new transit system: Evidence from New York City's ferry service." *Regional Science and Urban Economics*.
- Velásquez, Daniel. 2023. *Transit infrastructure, couples' commuting choices, and gender inequality*. Technical report. Working Paper.
- Warnes, Pablo Ernesto. 2024. *Transport infrastructure improvements and spatial sorting: Evidence from Buenos Aires*. Technical report. Working paper.
- Weiwu, Laura. 2025. *Unequal access: Racial segregation and the distributional impacts of interstate highways in cities*.
- Wong, Maisy. 2018. "A tractable approach to compare the hedonic and discrete choice frameworks." *Journal of Housing Economics* 41:135–141.
- Zárate, David R. 2023. *Spatial Misallocation, Informality and Transit Improvements: Evidence from Mexico City*. Technical report.