Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification*

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February 2021

Abstract

Los Angeles built a large rail transit system from scratch starting in 1990. I estimate that commuting between locations that both receive a station increases 16% by 2000 using panel data on bilateral commuting flows. A spatial general equilibrium model isolates non-commuting effects of transit and measures welfare. Local innovations interacted with intraurban geography identify key model parameters; estimates suggest inelastic labor mobility and housing supply. Metro Rail increases welfare by a baseline $94 million annually by 2000, or 12–25% of annualized operational subsidies and capital costs. Though more recent data indicate additional commuting growth, results highlight the challenge of providing transit to a car-oriented city with disperse commuting patterns and restrictive zoning.

Keywords: subway, commuting, gravity, economic geography, local labor supply
JEL Codes: J61, L91, R13, R31, R40

*Many have provided valuable advice during the development of this paper; I would especially like to thank Elliot Anenberg, Valerie Bostwick, Jeff Brinkman, Olivier Deschênes, Jonathan Dingel, Gilles Duranton, Jessie Handbury, Xavier d'Haultfœuille, Stephan Heblich, Kilian Heilmann, Nicolai Kuminoff, Jeff Lin, Kyle Meng, Yuhei Miyauchi, Paulina Oliva, and Wei You, as well as several anonymous referees. First draft was December 10, 2015.

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1 Introduction

High commuting costs limit consumer choice and mobility within cities. Governments invest large sums in urban rail transit infrastructure to mitigate the costs of distance and congestion. What are the benefits of these investments, and do these benefits come from changes in commuting behavior or other margins?

I study the effects of Los Angeles Metro Rail on commuting, non-commuting margins, and welfare. I assemble data on census tract-to-census tract commuting flows in 1990 and 2000 and develop a new approach to measure the effects of transit on commuting using these flows. Identification of the commuting effect exploits the bilateral and panel aspects. To study the non-commuting effects of infrastructure and quantify welfare impacts, I describe a quantitative spatial general equilibrium model and develop a new strategy to identify its key parameters.

The commuting effect is estimated from a panel gravity equation that embeds in the quantitative model. Instead of comparing single locations, identification of the commuting effect hinges on selecting *pairs* of locations that satisfy treatment ignorability. In practice, this means comparing changes in flows between pairs of locations that both receive treatment to changes in flows between pairs of locations in which just one, or neither, receives treatment. I leverage unanticipated shocks to route construction, historical streetcar routes, and proposed subway lines to limit selection concerns.[1] The commuting effect is substantial: commuting increases 11%–16% between connected tract pairs that both contain stations by 2000. Slightly more distant pairs see increases of 8%–14%; there is no effect further away. I also find some evidence of congestion improvements.

The model distinguishes the commuting effect of transit from non-commuting effects. Non-commuting effects impact all residences and workplaces near a station, rather than just commuters using transit-served routes. Conditional on model parameters and panel bilateral commuting data, panel data on local housing and labor prices map to time-varying, tract-specific primitives that represent non-commuting fundamentals (e.g., productivity, amenities). I then estimate the effect of transit on changes in these fundamentals. The commuting effect dominates; impacts from non-commuting channels appear minimal.

The model quantifies welfare and accounts for general equilibrium adjustments. Panel data on average wage and industry mix *at place of work* identify key model parameters.[2] Foremost is the local (extensive-margin) elasticity of labor supply to a tract, which governs how responsive agents are to changes in prices, amenities, and commuting costs. It is also essential for translating treatment effects to welfare. Estimates indicate a low value, implying agents heterogeneous in their preferred locations and relatively unwilling to move in response to changes in local characteristics. I also interact local labor demand shocks with the spatial configuration of the city to

1. See Redding and Turner (2015) for a review of this challenge and common solutions.

2. In many quantitative urban settings, wage at workplace is unobserved and identification requires assuming that workplace wage perfectly determines employment conditional on employee market access (e.g., Ahlfeldt et al. 2015). I show that the implied wages from this approach poorly explain observed wages.

estimate a tract-scaled housing supply elasticity.

By 2000, LA Metro Rail generates a baseline \$94 million in annual surplus, or 12%–25% of the annualized cost of construction and net operating expenses. At moderate borrowing costs, a bootstrap 95% confidence interval of this benefit is 2%–64% of costs. Accounting for reduced congestion may add another \$132 million per year. Because commuting behavior may adjust slowly, I draw upon alternative data to test for changes in commuting after 2000. Tracts connected before 2000 see additional commuting growth of 9%-12% by 2015. If this additional commuting growth is due to slow habituation, surplus is \$76 million higher annually than baseline. Though substantial, the commuting benefit of LA Metro Rail does not clearly exceed its cost over its first two decades, highlighting the difficulty in shifting commuting behavior in restrictively zoned, car-oriented cities.[3] Had zoning allowed 10% greater residential density near transit, the benefits of transit would have doubled.

This approach bridges the hedonic method of valuing transportation infrastructure (e.g., Baum-Snow and Kahn 2000; McMillen and McDonald 2004) with a generalized form of the travel time-based method typical of quantitative urban models (e.g., Monte, Redding, and Rossi-Hansberg 2018; Tsivanidis 2018). The hedonic method gives a real estate-mediated measure of the overall effect of transit due to both commuting and non-commuting margins, but cannot disentangle these margins nor account for general equilibrium effects.[4] In contrast, quantitative urban models only allow changes in commuting accessibility *as measured by travel time* to impact the relative attractiveness of locations.[5] Instead, I directly use commuting flows and allow transit to have non-commuting effects. Commuting flows reflect travel time, but also capture any other hard-to-measure, route-specific characteristics of commute choice, such as pleasantness or reliability. Furthermore, their use does not require imputing historical travel times.

Los Angeles is a populous, car-oriented region that built an extensive rail network within a decade, so its experience may be more informative for many cities considering rail-based mass transit than evidence from older, denser cities. It is an active line of inquiry whether new mass transit infrastructure in less dense cities provides appreciable benefits, particularly given the newer role of cities as centers of consumption in addition to production (Baum-Snow, Kahn, and Voith 2005). There is therefore a budding line of research examining the economic consequences of LA Metro Rail.[6]

3. There are three important caveats. First, while I calculate the commuting effects over a 25-year window, I only examine other channels from 1990 to 2000 due to data limitations. Second, the welfare analysis assumes that agents have homothetic preferences. Finally, transit may benefit non-commuting travel or have environmental effects on cities as a whole. I discuss these in Section 9.

4. Equilibrium effects (e.g., price spillovers) violate the stable unit treatment value assumption and can invalidate hedonic analysis. Donaldson and Hornbeck (2016) highlight the importance of equilibrium adjustments when evaluating transportation infrastructure.

5. These models may permit agglomerative amenities and productivity to respond to transit.

6. Schuetz (2015) shows little change in employment near new stations, and Schuetz, Giuliano, and Shin (2018) ask whether zoning hinders transit-oriented development. Redfearn (2009) documents heterogeneity in the capitalization of transit amenities.

I describe the setting in Section 2 and data in Section 3. Section 4 discusses identification and estimation of the commuting effect. Section 5 develops and characterizes the model. Section 6 turns to the second identification challenge: recovering the elasticities that parameterize the model. I describe estimating the non-commuting effects of transit in Section 7. Section 8 reports baseline welfare analysis, and Section 9 discusses extensions.

2 Setting: Commuting and transit in Los Angeles

Automobiles have long been a common feature of mobility in Los Angeles. Angelenos adopted automobiles in large numbers during rapid urban growth in the 1920s, leading to early complaints of crowded streets and attempts to relieve traffic delays (Fogelson 1967). Increasing congestion in the 1960s and 1970s led to several failed referendums to expand rail transit.

By 1980, the situation reached a political tipping point. The average trip took one-third longer than the uncongested time, three times the national average delay (Schrank et al. 2015). County voters passed Proposition A in 1980, a sales tax increase partially dedicated to transit. The plan would combine heavy rail (subway) and light rail operations to create an interconnected urban rail transit system. Construction began in 1985.

The first light rail line (the Blue Line) partially opened in mid-1990 (construction delays meant it did not reach its urban termini until early 1991).[7] The subway portion experienced several routing changes and first opened in 1993. This line was expanded, with additional stations opening in 1996 and 1999 (the subway is now run as two lines, Red and Purple). Another light rail line initially meant to connect to the international airport (the Green Line) opened in 1995 largely in the median of a new freeway, but without reaching the airport. The system continues to grow, with 6 lines, 93 stations, and 106 miles of rail as of 2016.

3 Data

I develop a panel of tract-level outcomes in 1990 and 2000 that covers Los Angeles County and four adjacent counties (Orange, Riverside, San Bernardino, and Ventura). This five-county area is economically distinct from nearby conurbations and captures most relevant local interactions. While there is a rich amount of data available, there are some difficulties in obtaining consistent variables over the sample period. I briefly discuss primary data sources; additional details can be found in the Appendix.

Geo-normalization. The standard unit of observation is a census tract or tract pair using 1990 Census geography. I normalize to 1990 geography because it minimizes rounding errors. I areally weight more recent geographies when crosswalking to 1990 tracts.

7. LA Metro Rail's line names recently changed. I use the older designations for continuity.

Commuting flow data. Tract-to-tract commuting flow data are primarily from the 1990 and 2000 Census Transportation Planning Packages (CTPP). I normalize origin-destination pairs to 1990 geography to create a consistent panel of tract-to-tract commuting flows. I apply consistent rounding and suppression rules when combining data across years. I use a similar dataset covering 2002 and 2015 from the LEHD Origin Destination Employment Statistics (LODES), normalized to 2010 geographies, in Section 9. Because of methodological differences in data collection, I do not combine CTPP and LODES data.

Place of residence and place of work data. Data on residential census tracts and block groups are from the National Historic Geographic Information System (NHGIS). I also use Geolytics' Neighborhood Change Database (NCDB). The CTPP contains *tract of work* wage data unavailable elsewhere and employment by industry (in 18 aggregate Standard Industrial Classification (SIC) codes). I trim the data to exclude implausible changes between 1990 and 2000 levels.

Transit data and treatment; other data sources. I combine geodata on Metro Rail transit stations and lines from the Los Angeles County Metropolitan Transportation Authority (LACMTA) with published information on the timing of station and line openings. To construct labor demand shocks, I draw from IPUMS microdata on all workers outside of California from the 1990 and 2000 Censuses. Panel land use data are from the Southern California Association of Governments (SCAG).

4 Commuting effects of LA Metro Rail

The number of commuters from residential tract i to workplace tract j at time t, denoted N_{ijt}, depends on residential tract characteristics, θ_{it}, workplace tract characteristics, ω_{jt}, and trip characteristics τ_{ijt}. Let T denote some function of proximity to transit. Commuting is:

$$N_{ijt} = N_{ijt}\Big(\theta_{it}(T_{it}), \omega_{jt}(T_{jt}), \tau_{ijt}(T_{it}, T_{jt})\Big) \tag{1}$$

The commuting effect of transit isolates transits effect from connecting i and j: $\frac{\partial N}{\partial \tau}\frac{\partial \tau}{\partial T}$. Transit can generally shift residential or workplace characteristics as well. Simple regression of commuting flows on transit does not differentiate commuting effects from other margins.

Bilateral and temporal aspects of panel flow data aid identification. Bilateral data allow flexibly controlling for residential and workplace characteristics and shocks. Temporal variation allows controlling for time-invariant pair-specific characteristics. Let T_{ijt} denote proximity to transit at both i and j. I estimate:

$$\ln(N_{ijt}) = \omega_{jt} + \theta_{it} + \varsigma_{ij} + T'_{ijt}\lambda^D + \iota_{s_i s_j t} + x'_{ijt}\beta + \varepsilon_{ijt} \tag{2}$$

where ς_{ij} are pair fixed effects. Because residential and workplace tract-by-year fixed effects (θ_{it}

and ω_{jt}) capture non-commuting effects of transit, λ^D is the commuting effect of transit. Equation (2) is a panel gravity equation, where distance is subsumed by the pair fixed effects.[8] These fixed effect also capture unobserved determinants of commuting flows—such as bus service, ease of parking, pleasantness, or even workplace-residential matching—to the extent that such features are time invariant. Some specifications use subcounty-by-subcounty-by-year fixed effects ($\iota_{s_i s_j t}$) to capture regional shifts in commuting patterns and allow flexible trends in regional integration. Though there are few observable, time-varying, pair-specific covariates to include in x_{ijt}, one is potentially important here: highway proximity (the Century Freeway opened in the mid-1990s).

I define treatment as proximity of *both a residential and a workplace tract* to LA Metro Rail stations using three mutually exclusive, binary definitions of treatment:

i) *O & D contain station*: Both tracts either contain a transit station or have their centroid within 500 meters of a transit station.

ii) *O & D <250m from station*: Some part of *both* tracts are within 250 meters of a transit station, but i) is not true.

iii) *O & D <500m from station*: Some part of *both* tracts are within 500 meters of a transit station, but neither i) nor ii) are true.

Only stations open before the end of 1999 are considered.[9]

A unique feature of this setting is the use of panel commuting flow data. Instead, a common approach uses changes in travel time and an auxiliary gravity model to infer changes in commuting. Changes in travel time can be approximated by routing engines, lessening the requirements from survey data. However, such an approach ignores determinants of commuting other than travel times.

4.1 Identification

Equation (2) is a dyadic estimator for a difference-in-differences (DD) design supplemented with origin- and destination-by-year fixed effects. Identification requires parallel counterfactual trends: In the absence of treatment, commuting between treated and control tract pairs would have evolved similarly on average, *conditional on separable changes to residential and workplace locations*. This substantially relaxes standard DD identification. Time-varying origin and destination fixed effects

8. $N_{ijt} = 0$ for some observations, so $\ln(N_{ijt})$ is undefined. I estimate high-dimension fixed-effects Poisson PML models to show robustness (Larch et al. 2019). Results are broadly consistent with the log-linear specification because most pairs that are ever zero are always zero, and always-zero pairs separate out with pair fixed effects. Thus, persistent zeros in panel commuting data are less problematic than in the cross-section.

9. Common maximum walking-to-transit distances in the planning literature are 400m and 800m (see, e.g., Daniels and Mulley 2013). The median tract in my sample is 1.38km^2. Were all tracts square with this area and population uniformly distributed, under i) average distance to a station is 444m–888m, under ii) it is 689m–888m, and under iii) it is 901m–1219m; see Appendix A.4.

largely control for the non-random siting of transportation infrastructure and other confounding shocks (e.g., school quality, zoning, etc.)

Identification is instead threatened by the placement of transit to connect pairs of locations that would have experienced differential changes in commuting anyway. I limit selection concerns with two approaches. First, I use historical data giving the locations of a proposed subway network and former streetcar lines, which embed shocks to route placement. This approach selects pairs of tracts that could have plausibly received transit by 2000 and share common historical land use and transportation characteristics that influence urban outcomes to this day. The second approach only considers tract pairs that are both existing or not-then-built transit stations, comparing pairs along the same subway line with pairs are not.

History & Shocks designs

Kelker, De Leuw & Co. (1925) designed a rail transit network to accommodate Los Angeles' booming population in the 1920s. The plan was defeated largely because of skepticism over private rail management and local opposition to elevated portions of the line.[10] Kelker, De Leuw & Co. (1925) also show active Pacific Electric Railroad (PER) lines (the PER was an at-grade railway system that served Los Angeles). I define two samples as the union of tract pairs near LA Metro Rail by 2000 and pairs that lie near: (i) the Kelker, De Leuw & Company subway proposal, "1925 Subway Plan"; or (ii) PER lines, "PER Sample". The 1925 Subway Plan itself has two variants: an *Immediate* plan meant to be built right away, and the full plan meant to accommodate buildout (*All*). Maps from Kelker, De Leuw & Company (1925) are shown in Figure 1; maps showing the research designs and modern lines and stations are in Figure 2.

The validity of these groups as controls is supported by several lines of reasoning and evidence. First, many control pairs contain one 'end' (either the origin or destination) that is treated, though the other end is not. Such control pairs compare changes in the number of commuters residing in i who work in j (which receives a transit linkage) to the number who work in j' (which does not). Similarly, workers in j who reside in i are compared with those who reside in i'. These comparisons control for many potential unobserved motives for changing commuting behavior. Control tracts selected by this approach are near historical transit corridors, illustrating one such channel. Brooks and Lutz (2019) find that locations near historical streetcar routes show greater density even today than other areas; the difference has also grown over time. Locations selected as controls are likely to be on similar land use trajectories as treated locations, and land use itself can have an impact on travel behavior (Duranton and Turner 2018).

Second, there was significant variation in timing and prioritization of route construction, due largely to reasons orthogonal to transit demand. Most notably, a geologic shock limited westward expansion of the Red/Purple Line. Its original routing was along Wilshire Boulevard, one

10. The system was to be run by Southern Pacific Railroad, which had a significant (perhaps overlarge) influence on kicakl politics (Fogelson 1967). Many of its alignments are part of LA Metro Rail.

of the densest corridors in Los Angeles. Methane seepage into a nearby clothing store exploded on March 24, 1985, leading to federal legislation restricting tunneling along Wilshire. This corridor appears as in both the 1925 Subway and PER samples (and in almost every transit plan since the 1920s). The Green Line's route was chosen to minimize construction costs by lying partially within an under-construction highway. Its westward end was first meant to connect to Los Angeles International Airport (LAX), but concerns about electromagnetic interference from the Federal Aviation Administration disrupted this alignment, leading to a more southerly route. Construction is underway on connections between the system and the Wilshire corridor and LAX, so these shocks can be seen as generating plausibly exogenous variation to the timing of treatment.

Route determination also reflects other factors besides transportation patterns. Routes were designed to satisfy political pressures, ensure political support for allocating revenue to rail projects, and spur political favor from one of the two local oversight agencies.[11] To illustrate, politicians demanded that heavy rail serve the San Fernando Valley, despite the cost and difficulty of doing so. It was also deemed necessary to connect Long Beach to ensure access to its portion of state gas tax revenue. At one point, a particularly serpentine route was dubbed the 'wounded knee' because it touched so many local political jurisdictions. In sum, Elkind (2014, p. 50)'s statement that "politics, outside circumstances, and the geography of power ... played an outsized role in influencing where the new rail lines would go" indicates the presence of factors unrelated to travel demand in the planning process.

Finally, I provide econometric evidence. While the data do not permit testing pre-trends in *tract-pair* flows, I examine pre-trends in *tract*-level housing and labor market characteristics using NCDB data from 1970 to 1990.[12] Among economic variables later captured in the model (columns 1–4 of Appendix Table H1), there are no significant differences in pre-trends in employed residential population or household income in any sample. One sample (PER) shows a pre-trend in housing values, and three have pre-trends in number of households. However, the Immediate 1925 Subway Plan sample shows no evidence of differential pre-trends in any model-relevant characteristic (and so is the preferred specification). Regardless, the fixed effects in Equation (2) render it robust to tract-level pre-trends.

I also investigate differential trends in neighborhood and travel characteristics (columns 5–10 of Appendix Table H1). In some samples, residents of treated tracts were becoming less college educated and more impoverished, and were moving less often. Evidence on differences in travel pre-trends is mixed: in two samples, the share of household with no cars was decreasing prior to treatment. In none of the samples was the commuting share by auto differentially changing, but in all samples the relative transit commuting share transit was increasing slightly. The Immedi-

11. The political setting is presented in Elkind (2014), who notes that "plotting a subway through the politically decentralized landscape of Los Angeles meant ceding control to numerous fiefdoms of federal, state, and local politicians" (p. 70).

12. NCDB is, by default, normalized to 2010 geographies. I use the same treatment rules, but this results in higher observations counts due to denser tracts in 2010 than 1990.

ate 1925 Subway Plan sample shows the least evidence of pre-trends across all variables. While tract-level pre-trends do not impede identification of the commuting effect, the non-commuting analysis addresses this; see Section 7.

Same Line designs

The Same Line designs compare tract pairs on the same line to tract pairs that lie along different lines. This design expects that tract pairs along the same line are "more treated" than those that are not. Parallel trends in this design are violated if planners targeted directly connecting (by the same line) locations that would have seen larger increases in commuting anyway relative to other treated—but indirectly connected—locations.

I show two variants of this design. The first includes not only locations treated by 2000, but also locations not yet treated by 2000 but that are treated by 2015. In this 'Ever Treated' variant, treated pairs are those that both lie near stations along the same line and control pairs are those that both lie near a station open by 2015 but are not along on the same line. In the second, more stringent variant (Treated by 2000), I restrict control pairs to only those that lie near a station open by 2000.

There are two caveats regarding these designs. First, they only identify the average commuting effect of transit proximity if it is infinitely costly to switch from one line to the other (i.e., there is a high transfer penalty). Under a finite (but non-zero) transfer penalty, these designs reflect the marginal effect of being directly connected relative to indirectly connected. Second, these designs rely on fewer observations, and are less precise.

4.2 Commuting flow estimates

Table 2 reports estimates of λ^D on commuting flows between 1990 and 2000. Columns 1–3 show results from the full sample, successively adding in measures of treatment proximity, subcounty pair-by-year fixed effects, and controls. Columns 4–6 reflect the History & Shocks designs, retaining the richer specification of column 3. Columns 7–8 report results from the Same Line designs. Standard errors are clustered along three dimensions to be robust to correlation within tract pairs, residential tracts, and workplace tracts.

LA Metro Rail increased commuting 10%–22% between tracts nearest transit stations by 2000. Estimates are significant across all specifications. The preferred specification (column 6) indicates an increase of 14.9 log points (16%). Slightly less transit-proximate tract pairs see an effect of 8%–14%, with a preferred estimate of 12.8 log points (14%). Tract pairs at a further distance from stations see no significant effect.[13]

A few features of Table 2 deserve note. First, estimates are ordered by proximity. Second, estimates for the least proximate bin are insignificant. Together these form a specification test; we

13. See footnote 9 for interpretation of these distance bins and robustness in Appendix Figure H5. Similar estimates result from Poisson PML specifications; see Appendix Table H3.

expect effects concentrated near stations with little or no effect further away. Third, as the control group becomes more targeted (and sample size decreases), point estimates become larger (ascending from left to right). This ordering implies that control tract pairs experience progressively less commuting growth than in the full sample. As these designs increasingly select connections between older, more mature parts of the city, this is reasonable. Finally, Same Line estimates are a bit larger than the History & Shocks estimates, but also less precise. This suggests that proximity to directly connected stations is more important than simply being near a transit station.[14]

In this vein, the data allow further exploration. Interacted proximity bins for origin and destination tracts indicate a greater effect of proximity at the destination than the origin, suggesting commuters respond more to closer workplace-to-station proximity than to closer residence-to-station proximity (though estimates are noisy; see Appendix Table H5). Treatment does not generally alter the extensive margin of connection (zero vs. non-zero flows), but its effect may increase slightly over time (see Appendix Table H2; I discuss habituation more in Section 9). This may be evidence of delayed take up due to disruption related to construction.

4.3 Commuting time (congestion) estimates

A common motivation for urban rail transit is to relieve automobile congestion. Anderson (2014) finds that a labor strike that disrupted LA Metro Rail service in 2003 increased nearby automobile congestion by roughly 47%. However, that strike lasted 35 days. It is unclear how to map that short-run response to the long run. Duranton and Turner (2011) find no aggregate evidence that transit decreases automobile travel. This notion, called the 'Fundamental Law of Congestion' after Downs (1962), suggests that improvements to congestion (and downstream benefits like air pollution) may be transitory. Under this view, a primary role of transit is to enable a larger urban population.

I combine reported CTPP travel times with inferred travel routes to test the persistence of decreased congestion due to transit.[15] I map the fastest driving route between all location pairs in my sample and calculate the share of each route that falls within five mutually exclusive distance buffers. After merging with reported average travel times, I analyze LA Metro Rail's impact on travel times using the following specification:

$$\ln(\tau_{ijt}) = \sum_{k} \lambda_{\tau,k} \frac{\ell_{ij\in k}}{\ell_{ij}} 1_{[t=2000]} + \omega_{jt} + \theta_{it} + \varsigma_{ij} + \varepsilon_{ijt} \tag{3}$$

where τ_{ijt} is the average reported travel time from i to j in year t. I use the same fixed effects regime as before to isolate pair-specific changes due to route exposure to transit.

14. Appendix Table H4 directly tests this. Though noisy, effects are always larger for locations along the same line.

15. The setting is somewhat comparable to Anderson (2014), though he uses a different research design and focuses primarily on observed highway travel speeds.

Table 3 shows results for two measures of travel time: log average travel time across all modes, and log average travel time for private cars.[16] Results for all-mode travel times are negative but mostly insignificant; these may reflect mode switching to transit. Car-only results, however, show clear evidence of a reduction in travel time. With subcounty pair-by-year fixed effects, routes that are entirely within 250m meters of lines by 2000 see a 15.0 log point (14%) reduction in travel time. For routes lying entirely between 250m–500m from lines by 2000, travel times decrease by 18.9 log points (17%). Though not statistically different, the larger effect slightly further from the rail lines may indicate slower travel due to at-grade crossings. Portions of routes that lie further than 500m from a rail line see no change in travel times.

The estimates in columns 3–4 of Table 3 are roughly one-third those in Anderson (2014). This suggests substantial but incomplete attenuation of congestion benefits over a period of 5–10 years, indicating that congestion benefits of transit may not be entirely transitory. Any downstream benefits, like improved air quality, may similarly last over longer time horizons.

5 A model of urban location choice

I turn to a quantitative urban model of residential and workplace choice to recover the non-commuting effects of transit and translate the effects of transit to welfare. The model links local, observable equilibrium outcomes to local, unobservable economic fundamentals (e.g., productivity, amenities). The model includes a collection of N locations in a city, operationalized as census tracts, that each contain a labor market and a housing market.

The model is similar to that of Ahlfeldt et al. (2015), with five differences: (i) origin-destination pairs can differ in mean utility, which permits deriving Equation (2) from the model; (ii) a local housing efficiency parameter captures differences in local regulations and per unit housing costs; (iii) land use between housing and production is exogenously determined; (iv) endogenous externalities are omitted from the primary model[17]; and (v) the model can be transparently rewritten as a system of three equations log-linear in data and fundamentals. The first two generalize Ahlfeldt et al. (2015), while the second two are simplifications that match the empirical setting and have little quantitative impact. Differences (i) to (iii) lead to (v); linearity simplifies exposition and estimation.

16. Samples sizes are smaller than in Table 2 primarily due to disclosure restrictions, which is also why the sample for private car travel time is smaller than travel time across all modes. I also drop pairs for which the implied trip speed is greater than 80mph.

17. In the Appendix, I include endogenous agglomeration. I later discuss how endogenous agglomeration alters the model and results.

Joint market household decision: Labor supply and housing demand

Atomistic households make consumption decisions and choose a tract of work and a tract of residence. Conditional on residential location i, households face per-unit housing costs Q_i and receive amenity $\tilde{B}_i$. Conditional on place of work j, households inelastically provide one unit of labor in exchange for wage W_j. Given locations and prices, households make decisions over consumption of housing and a composite good. Specifically, household o chooses location pair ij, consumption $\mathcal{C}$, and housing H to maximize Cobb-Douglas utility:

$$\max_{\mathcal{C},H,\{ij\}} U_{ijo} = \max_{\mathcal{C},H,\{ij\}} \frac{\nu_{ijo}\tilde{B}_i}{\delta_{ij}} \left(\frac{\mathcal{C}}{\zeta}\right)^{\zeta} \left(\frac{H}{1-\zeta}\right)^{1-\zeta} \quad \text{s.t.} \quad \mathcal{C} + Q_i H = W_j$$

where ν_{ijo} is household o's idiosyncratic preference for location pair ij. The commuting cost between i and j is captured by $\delta_{ij} \geq 1$. The share of household expenditures on housing is $1-\zeta$. Indirect utility conditional on location pair ij is:

$$v_{o|ij} = \frac{\nu_{ijo}\tilde{B}_i W_j Q_i^{\zeta-1}}{\delta_{ij}}$$

Housing consumption for o conditional on ij is $H_{ijo} = (1-\zeta)W_j/Q_i$.

I assume ν_{ijo} is distributed Fréchet with scale parameter $\tilde{\Lambda}_{ij} = T_i E_j D_{ij}$ and shape parameter $\epsilon > 0$. The cdf of ν is thus: $F_{ij}(\nu) = e^{T_i E_j D_{ij} \nu^{-\epsilon}}$. The scale parameter captures mean idiosyncratic preference for location pair ij: T_i captures the mean utility of residing in i, E_j the mean non-wage utility of working in j, and D_{ij} an unobserved pair-specific shift in the utility of a particular commute. The shape parameter governs the degree of homogeneity in preferences: For high ϵ, agents view location pairs homogeneously, while for low ϵ, their valuations are heterogeneous. The share of the population that chooses residential location i and place of work j under the Fréchet assumption is:

$$\pi_{ij} = \frac{\tilde{\Lambda}_{ij}\left(\delta_{ij}Q_i^{1-\zeta}\right)^{-\epsilon}(\tilde{B}_i W_j)^{\epsilon}}{\sum_r \sum_s \tilde{\Lambda}_{rs}\left(\delta_{rs}Q_r^{1-\zeta}\right)^{-\epsilon}(\tilde{B}_r W_s)^{\epsilon}} \tag{4}$$

Observable commuting flows are $N_{ij} = \pi_{ij}\bar{N}$, where $\bar{N}$ is total population.

The city can be viewed either as existing in autarky or being nested in a large, open economy. This assumption makes little difference outside of welfare calculations (due to homothetic preferences). In an open economy, no spatial arbitrage requires that the average welfare from moving to the city equal the reservation utility of living elsewhere. The expected value of moving to the city is:

$$\mathbb{E}[U_{ijo}] = \Gamma\left(\frac{\epsilon - 1}{\epsilon}\right) \cdot \left[\sum_r \sum_s \tilde{\Lambda}_{rs} \left(\delta_{rs} Q_r^{1-\zeta}\right)^{-\epsilon} (\tilde{B}_r W_s)^{\epsilon}\right]^{1/\epsilon} \tag{5}$$

where $\Gamma(\cdot)$ is the gamma function and the aggregate population $\bar{N}$ is given or implicitly defined. Under free mobility $\mathbb{E}[U_{ijo}] = \bar{U}$ and aggregate population changes to maintain $\bar{U}$.

Production: Labor demand

Measure-zero firms produces a globally tradable commodity in each location j under perfect competition. Firms select labor N^Y and land L^Y inputs to maximize profits under constant returns to scale. Production is multiplicatively separable in local productivity A_j and a technology that is identical across j: $Y = A_j F(N_j^Y, L_j^Y)$. Because of the atomistic size of firms, land use decisions are made in accordance with profit maximization despite the locally fixed quantity of land. Perfect competition in labor markets implies that firms pay workers the marginal product of labor: $W_j = A_j F_N(N_j^Y, L_j^Y)$. I assume Cobb-Douglas production technology: $F(N^Y, L^Y) = (N^Y)^{\alpha}(L^Y)^{1-\alpha}$. Inverse labor demand is given by:

$$W_j = \alpha A_j \left(\frac{L_j^Y}{N_j^Y}\right)^{1-\alpha} \tag{6}$$

Housing supply

Measure-zero builders construct housing using land L^H and material inputs M. A local, multiplicatively separable housing productivity term $\tilde{C}_i$ captures cost drivers such as geography and regulation. Materials are readily available in all locations at the same cost, but local land supply for housing is predetermined.[18] Convexity in land pricing serves as a congestive force, driving up prices in desirable locations until agents look elsewhere. I specify Cobb-Douglas housing production: $H = (L^H)^{\phi} M^{1-\phi} \tilde{C}_i$. Developers sell housing in location i in a competitive market at unit price Q_i to maximize profit: $Q_i H - P_i^L L^H - P^M M$. The price of construction materials P^M is exogenous and common to all locations.

Because detailed data on housing production are not available, I utilize a zero-profit condition to develop an empirical formula for housing costs. The first-order condition for developer profits with respect to construction materials gives:

$$Q_i = \frac{P^M}{(1-\phi)\tilde{C}_i} \left(\frac{M}{L^H}\right)^{\phi} \tag{7}$$

18. This simplifies the model while maintaining fidelity to the setting. Strong zoning and the medium-run time frame of this study may not match the temporal patterns required for land use change.

Substituting this into the developer's profit function and enforcing zero-profit conditions gives construction material demand, $M^* = \frac{1-\phi}{\phi}\frac{L^H P_j^L}{P^M}$, as well as $Q_i = (P_i^L L^H + P^M M)/((L_i^H)^\phi M^{1-\phi}\tilde{C}_i)$. Substituting in M^* gives the cost function: $Q_i = C_i(P_i^L)^\phi$, where $C_i = (P^M)^{1-\phi}/(1-\phi)^{1-\phi}\phi^\phi\tilde{C}_i$ captures the inverse efficiency in housing production.

The price of land, P_i^L, responds to changes in demand and land availability: I parameterize it as a function of local housing density $P_i^L = (H_i/L_i^H)^{\tilde{\psi}}$, where the parameter $\tilde{\psi} > 0$ captures local price elasticity of land with respect to density. This parameter provides a congestive force to the model. Combining the expression for land price with Equation (7) relates housing supply, price, and land availability:

$$Q_i = C_i\left(\frac{H_i}{L_i^H}\right)^\psi \tag{8}$$

where $\psi = \tilde{\psi}\phi$. As housing productivity $\tilde{C}_i$ increases, C_i falls, so increases in housing productivity (decreases in C_i) increase the quantity of housing supplied at any price.

Equilibrium characterization

In equilibrium, labor and housing markets clear in all locations. Labor market clearing requires that demand equal supply locally:

$$N_i^Y = \sum_r \bar{N}\pi_{ri} \tag{9}$$

Given Cobb-Douglas preferences, housing demand is a constant fraction of the ratio of wage to housing price. Aggregate housing demand in i is the sum of wage-rent ratios weighted by commuting flows, reflecting heterogeneity in income stemming from variation in wage (i.e., place of work). Housing market clearing requires that the local housing supply equal demand:

$$H_i = (1-\zeta)\sum_s \bar{N}\pi_{is}\frac{W_s}{Q_i} \tag{10}$$

Given model parameters $\{\alpha, \epsilon, \zeta, \psi, \kappa\}$, reservation utility $\bar{U}$, vectors of land availability by use $\{\mathbf{L^Y}, \mathbf{L^H}\}$, vectors of residential fundamentals $\{\tilde{\mathbf{B}}, \mathbf{C}, \mathbf{T}\}$, vectors of place of work fundamentals $\{\mathbf{A}, \mathbf{E}\}$, and matrices of residential-place of work pair fundamentals $\{\mathbf{D}, \boldsymbol{\tau}\}$, an equilibrium is referenced by price vectors $\{\mathbf{W}, \mathbf{Q}\}$, commuting vector $\boldsymbol{\pi}$, and scalar population measure $\bar{N}$.

Proposition 1. *Consider the equilibrium defined by Equations (4), (6), (8), (9), (10):*

i) At least one equilibrium exists across residential locations with strictly positive quantities of residential land and work locations with strictly positive quantities of land used in production.

ii) There is at most one equilibrium if

$$\frac{2\epsilon(\epsilon+1)(1-\alpha)(1-\zeta)}{1+\epsilon(1-\alpha)} - 1 \leq \frac{1}{\psi} \tag{11}$$

Proof. See Appendix. □

Inversion

Though the model may have multiple equilibria, for a given set of parameters, there is a unique mapping from the observed data to local fundamentals. Model parameters are estimated using these fundamentals and the observed values of the endogenous variables in combination with instruments to define moment conditions. $\tilde{B}_i$ and T_i enter isomorphically; let $B_i = T_i \tilde{B}_i^{\epsilon}$ and $\Lambda_{ij} = B_i E_j D_{ij}$.[19] Local fundamentals $\mathbf{A}$, $\mathbf{C}$, and $\mathbf{\Lambda}$ can be expressed as unique functions of data and parameters:

Proposition 2. *Given parameters* $\{\alpha, \epsilon, \zeta, \psi, \kappa\}$, *observed data* $\{\mathbf{W}, \mathbf{Q}, \boldsymbol{\pi}, \bar{N}\}$, *and commuting times* $\boldsymbol{\tau}$, *then there exists a unique set of fundamentals* $\{\mathbf{A}, \mathbf{C}, \mathbf{\Lambda}\}$ *that are consistent with the data being an equilibrium of the model.*

Proof. See Appendix. □

6 Identification and estimation

Local labor and housing market elasticities provide a mapping between local fundamentals (and interventions that shift them) and observed prices and quantities. Consistent estimates of the elasticities are required to use observable data to learn about changes to local fundamentals and to simulate counterfactual scenarios. I develop an identification strategy that uses panel variation in wages at place of work, housing prices, and commuting flows, permitting the use of fixed effects to control for unobserved, time-invariant characteristics that confound identification (for example, location near a port, on a pleasant hillside, or in town with stringent land use regulations).[20]

All components of the model are expressed in the commuting flow (4), wage setting (6), and housing price (8) equations. Denote log values in lowercase letters. Adding time subscripts and including tract and tract-pair fixed effects (e.g., $\ln(A_{jt}) = \bar{a}_j + a_{jt}$), these equations deliver a

19. This mapping diverges from Ahlfeldt et al. (2015), where local fundamentals consist of a composite workplace term that combines $\mathbf{A}$ and $\mathbf{E}$, a residential term that combines $\mathbf{B}$ and $\mathbf{T}$, and omits location or pair specific variation in housing supply $\mathbf{C}$ or commute utility $\mathbf{D}$. The components of $\mathbf{\Lambda}$ are not uniquely identified from the data; I use statistical arguments to separate $\mathbf{B}$, $\mathbf{E}$, and $\mathbf{D}$.

20. Persistent, difficult-to-measure amenities play an anchoring role in cities (Lee and Lin 2018). Strong land use regulation likely locks in such anchors in Southern California (Severen and Plantinga 2018).

tractable system log-linear in data and fundamentals (see Appendix):

$$\begin{aligned}
\text{Labor demand:} \quad & w_{jt} = g_{0t} + \tilde{\alpha} n^{Y}_{jt} + \bar{a}_j + a_{jt} && (12)\\
\text{Commuting:} \quad & n_{ijt} = g_{1t} + \underbrace{\epsilon w_{jt} + \bar{e}_j + e_{jt}}_{\substack{=\omega_{jt},\\ \text{Labor supply}}} + \underbrace{\tilde{\zeta} q_{it} + \bar{b}_i + b_{it}}_{\substack{=\theta_{it},\\ \text{Housing demand}}} - \epsilon\kappa\tau_{ijt} + \bar{d}_{ij} + d_{ijt} && (13)\\
\text{Housing supply:} \quad & q_{it} = g_{2t} + \psi h_{it} + \bar{c}_i + c_{it} && (14)
\end{aligned}$$

where n^{Y}_{jt} is log employment density, h_{it} is log housing density, the g are constants, and $\tilde{\alpha} = \alpha - 1$ and $\tilde{\zeta} = -\epsilon(1-\zeta)$. Local fundamentals are potentially functions of covariates ($\bar{a}_j + a_{jt} = a(x_{it})$ and so on), such as transit proximity. Equation (13) offers a structural interpretation of Equation (2) and its fixed effects: $\omega_{jt} = \epsilon w_{jt} + \bar{e}_j + e_{jt}$ and $\theta_{it} = \tilde{\zeta} q_{it} + \bar{b}_i + b_{it}$.

6.1 A general approach to identifying local elasticities

I develop a local implementation of a shift-share instrument to overcome simultaneity in Equations (12)–(14). I leverage plausibly exogenous panel variation in tract-level labor demand, interacting local labor demand shocks with the distance between tracts to create variation in exposure to local economic shocks. I focus on identification of ϵ (the elasticity of labor supply) and ψ (the inverse elasticity of housing supply), as these two embed information about the local economic environment and cannot be calibrated from microdata.[21]

Identification requires a demand or supply shock that shifts one of Equations (12)-(14) but is excludable from the others. I construct tract-level labor demand shocks from changes in national wage and employment levels and ex ante local employment shares by industry. Effective variation comes from changes in wages and employment determined by ex ante local industrial composition. These shocks are relevant if they are correlated with changes in local productivity (Δa_{jt}) and excludable if they are uncorrelated with changes in the other local fundamentals. Under these assumptions, labor demand shocks trace out the labor supply curve. Housing demand in nearby locations shifts in response. Because this downstream housing demand response will be stronger nearer the workplace origination of the shock, I take a linear combination of labor demand shocks with weights determined by a spatial decay function and commuting to map labor demand shocks to a residential tract. This derived housing demand instrument traces out the housing supply curve.

Let $R^{q,Nat}_t$ be average national wage or total national employment in industry q in year t, $N^{q}_{j,0}$

21. I develop moment conditions that can identify all four housing and labor supply and demand elasticities in the Appendix. However, stronger assumptions are required to identify the demand elasticities. Briefly, for agents who work in j and live in i, a labor demand shock to agents who also live in i but work elsewhere (in j') shifts housing supply in i; a labor demand shock for workers $n_{ij'}$ translates into a spatially decayed housing supply shock to workers $n_{ij\neq ij'}$. Labor demand shocks in one location alter wages and induce workers to shift employment location, providing a labor supply shock.

be the number of workers in each two-digit SIC industry q in the initial year (1990) in tract j, and $N_{i,0} = \sum_q N^q_{j,0}$ the ex-ante total employment in tract i. The labor demand shock is formed by interacting changes in wages or employment with ex ante local employment shares and summing across industries:

$$\Delta z_{jt} = \sum_q \frac{R^{q,Nat}_t - R^{q,Nat}_0}{R^{q,Nat}_0} \cdot \frac{N^q_{j,0}}{N_{j,0}}$$

Because the demand shock embeds information on ex ante industry shares, an implicit identification assumption is that changes in non-productivity latent variables (e.g., amenities) are uncorrelated with prior industry structure. To ensure that local factors do not drive national changes, I exclude all workers in California.

6.2 The labor supply elasticity (Fréchet shape parameter)

The shape parameter ϵ governs the homogeneity of location preference, but is also an extensive-margin labor supply elasticity that conditions on commuting and residential geography. A straightforward approach to identifying ϵ is to instrument wage in Equation (13) with z_{jt}. Place of residence-by-year fixed effects (θ_{it}) control for changes in residential amenities that may be correlated with labor demand shocks, so the corresponding moment condition is:

$$\mathbb{E}[\Delta z_{jt} \times (\Delta e_{jt} + \Delta d_{ijt})] = 0, \; \forall i, j \tag{M-1}$$

However, identification can instead be achieved under a weaker assumption using a two-step process. First, estimate place of work-by-year fixed effects ($\hat{\omega}_{jt}$) from Equation (13). Then, use it as the dependent variable in the wage equation $\Delta\hat{\omega}_{jt} = \epsilon \Delta w_{jt} + \Delta e_{jt}$. Instrumenting wage with the labor demand shock in then identifies the labor supply elasticity if

$$\mathbb{E}[\Delta z_{jt} \times \Delta e_{jt}] = 0, \; \forall j. \tag{M-1a}$$

Moments conditions M-1 and M-1a require that the labor demand shock in a tract j be uncorrelated with unobservable changes in factors that shift labor supply to that same tract. These unobservable factors include changes in workplace amenities (or any workplace-specific labor supply shifter), e. M-1 also requires that the local labor demand shocks be uncorrelated with travel costs, d; M-1a does not.

Results and discussion

I use the two-step process to estimate ϵ under moment condition M-1a the the wage variant of the labor demand shock, as wage is the endogenous variable. Table 4 shows results using three different methods of recovering $\hat{\omega}_{it}$. Columns 1–2 estimate ω_{it} jointly using both years of data in a log-linear panel. Columns 3–4 use a separate Poisson PML model for each year to estimate ω_{it}, conditioning on bilateral travel costs. Columns 5–6 jointly using both years of data (like columns 1–2), but use the panel Poisson PML estimator with pair fixed effects. As such, columns 3–4 include all tract pairs with zero flows, columns 5–6 drop tract pairs that have zeros flows in both time periods, and columns 1–2 omit tract pairs with zero flows in any years (see footnote 8).

The first stage is significant, has the right sign, and is of a reasonable magnitude across all specifications.[22] Using the log-linear estimator of $\hat{\omega}$, estimates of ϵ are about 1. Unlike the commuting analysis, zeros make a large difference in estimates because any individual work tract may have many incoming zeros; incorporating this information into the fixed effect is important. Estimates of ϵ based on $\hat{\omega}$ from Poisson PML models vary between between 2.18 and 2.90. The inclusion of subcounty-by-year fixed effects in columns 4 and 6 identifies the effect more narrowly from subregional variation. I take $\epsilon = 2.18$ from Column 6 as the preferred estimate. The generally low value of ϵ implies that workers are quite heterogeneous in location preferences and is roughly in line with extensive-margin labor supply elasticities found in studies of labor markets. For example, Falch (2010) estimates labor supply elasticities between 1.0 and 1.9, Suárez Serrato and Zidar (2016) find values between 0.75 and 4.2, and Albouy and Stuart (2020) recover 1.98.

M-1 and M-1a are local, rather than citywide, moment conditions, and are substantially weaker than in standard applications of shift-share instruments. When an aggregate (citywide) labor demand shock is used to trace out aggregate labor supply, identification requires the shock be orthogonal to any non-wage determinants of labor supply, $\mathbb{E}[\Delta \bar{z}_t \cdot (\Delta \bar{b}_t + \Delta \bar{d}_t + \Delta \bar{e}_t)] = 0$ in my notation). where $\bar{\cdot}$ averages over locations within a city. This suggests potential pitfalls in standard applications of shift share instruments. First, changes in residential amenities, commuting costs, and workplace amenities must be uncorrelated with labor demand shocks *regardless of where in the city they occur*. Second, changes in amenities cannot be correlated with the labor demand shock, whereas in my design, even unobserved residential amenities are not confounding. Finally, in the standard design, changes in commuting costs cannot be correlated with labor demand shockd locally or elsewhere within the city. This would be violated if, e.g., growth in trucking created significant congestion. Moments M-1 and M-1a clarify the spatial requirements for identification and are robust to correlation with changes in residential amenities.

The urban economic geography literature typically identifies ϵ from a combination of model-

22. The first stage captures the transmission of national wage shocks to local wages, so a value near 1 is to be expected. Traditional F-statistics are well above the standard homoskedastic threshold of 10. A heteroskedasticity- and weak instrument-robust bootstrap 95% confidence interval is [0.562, 8.856] with a median value of 2.157; see Section 8 and Appendix D. Appendix Tables H6 and H7 provide specification tests from Goldsmith-Pinkham, Sorkin, and Swift (2020) that correspond to columns 5–6 of Table 4. The two industries with the largest Rotemberg weights are manufacturing and transportation; they account for about one-half of positive weights. Weights are related to national growth rates, but load more onto industry location. Encouragingly, industry-specific elasticities have similar means regardless of whether their weights are positive, and estimates (without fixed effects) are broadly similar across alternative estimators. Note that the data contain relatively few industrial categories, a trade off of the fine geographic scale.

ing assumptions and cross-sectional variation in travel time (or distance), often resulting in higher estimates of ϵ. For example, Ahlfeldt et al. (2015) condition on the marginal disutility of travel time estimated from an auxiliary model, then require two related cross-sectional assumptions: workplace utility must be orthogonal to workplace wage ($\mathbb{E}[w_j e_j] = 0$) and there can be no variation in (non-pecuniary) workplace utility ($\mathbb{E}[e_j^2] = 0$).[23] Such assumptions are not supported by the data. Panel A of Figure 3 plots ω_j (which is equal to $\epsilon w_j + e_j$) against w_j using data from Greater Los Angeles in 1990. If $\mathbb{E}[w_j e_j] = 0$, then the slope in Panel A of Figure 3 (0.17) is equal to ϵ. If $\mathbb{E}[e_j^2] = 0$, this figure would reveal a one-to-one mapping between ω_j and w_j. Instead, ω_j is more closely related to workplace employment levels (Panel B of Figure 3), highlighting the severity of simultaneity when wage is unobserved.[24] The value of ϵ is central for studying shocks to urban structure: Preference heterogeneity limits the responsiveness of agents to changing local conditions.

6.3 The (inverse) housing supply elasticity

A labor demand shock in one location shifts demand for housing in locations where workers might live, and thus can be used to identify the slope of the housing supply curve. This requires mapping the labor demand shock to residential locations. I describe a housing shock to residential location i of the form $\Delta z_{it}^{HD} = \mathbf{z}_t \cdot \boldsymbol{\vartheta}_i$, with weights ϑ that decay in travel time between locations that ever have positive commuting:

$$\Delta z_{it}^{HD}(\rho) = \sum_s \frac{e^{-\rho \delta_{is}} 1_{\check{n}_{is}>0} \Delta z_{st}}{\sum_s e^{-\rho \delta_{is}} 1_{\check{n}_{is}>0}}$$

where δ_{js} is the travel time between j and s, ρ is spatial decay, and $\check{n}_{is}$ denotes the maximum flow value from i to s in any year. With $\rho > 0$, labor demand shocks nearer a residential location i are more important than labor demand shocks farther from i. The resulting inverse-travel time weighted labor demand shock can be used to instrument housing density and identify ψ, the inverse price elasticity of housing supply, under the following condition:

$$\mathbb{E}[\Delta z_{it}^{HD}(\rho) \times \Delta c_{it}] = 0, \ \forall i \tag{M-2}$$

23. To see this, Ahlfeldt et al. (2015) assume $\mathbb{E}[(1/\epsilon)^2 \omega_j^2 - \sigma_w^2] = 0$, where $\omega_j = \epsilon w_j + e_j$ and σ_w^2 is observed wage dispersion. Rearranging, ϵ is identified if $\epsilon^2 \mathbb{E}[w_j^2] + 2\epsilon \mathbb{E}[w_j e_j] + \mathbb{E}[e_j^2] = \epsilon^2 \mathbb{E}[w_j^2]$.

24. Other papers take varied, ad hoc approaches to deal with unobserved workplace wages. For example, Monte, Redding, and Rossi-Hansberg (2018) assume an elasticity of substitution σ, specify a trade-in-goods model to recover productivity from cross-sectional trade flows, then assume recovered productivity is orthogonal to workplace and origin-destination specific amenities $\mathbb{E}[a_j(\sigma) \times (e_j + d_{ij})] = 0, \forall i, j$, implicitly requiring correct model specification. Notably, Kreindler and Miyauchi (2017) observe workplace wage and find a modest cross-sectional relationship between ω and w using cell data and travel surveys.

Although both elements of M-2 relate to tract i, the housing demand shock draws on labor demand shocks from any j (including i).

M-2 requires labor demand shocks be uncorrelated with changes in (inverse) housing productivity, Δc_{it}, which reflects the efficiency of housing provision. One potential concern with Assumption A-2 is whether local zoning responds to local labor demand shocks. An alternative version drops the most local component of the labor demand shock (from i itself):

$$\Delta z_{it}^{HD,a}(\rho) = \sum_{s \neq i} \frac{e^{-\rho \delta_{is}} 1_{\check{n}_{is}>0} \Delta z_{st}}{\sum_{s \neq i} e^{-\rho \delta_{is}} 1_{\check{n}_{is}>0}}$$

This identifies housing supply if $\mathbb{E}[\Delta z_{it}^{HD,a}(\rho) \times \Delta c_{it}] = 0, \ \forall i$, which can rewritten and more easily parsed as a function of the labor demand shock itself:

$$k_{ij} \mathbb{E}[\Delta z_{jt} \times \Delta c_{it}] = 0, \ \forall \ i \neq j \tag{M-2a}$$

where $k_{ij} = e^{-\rho \delta_{ij}} 1_{\check{n}_{ij}>0}$ is a weight. Condition M-2a requires innovations in housing efficiency be uncorrelated with nearby productivity shocks.

Results and discussion

Implementing these moment conditions requires choosing the spatial decay parameter, $\rho > 0$, governing how labor demand shocks propagate across space. I experiment with different values in $\ln(\rho) \in [-10, -2]$. I report results for $\ln(\rho) = -5.5$, estimated in differences using the employment instrument. Table 5 estimates the inverse housing supply elasticity in Equation 14 under M-2 (odd columns) and M-2a (even columns). First stage estimates (panel D) are significant and negative, indicating that a positive productivity shock decreases nearby residential density. Productivity shocks increase per worker demand for residential floorspace, which—given restrictive zoning in this area—manifests either as larger (likely single-family) homes or drives residential mobility to less dense housing options.

Estimates imply supply elasticities of 0.45–0.46 without income-driven adjustment in quantity (columns 1 and 2), and 0.57–0.62 when income can influence housing quantity (columns 3–6). Columns 3 and 4 provide a specification test for Equation (8).[25] Even columns exclude the own tract labor demand shock when aggregating the instrument (under M-2a); this permits local housing productivity to covary with the local labor demand shock. Estimates are similar. All results suggest that local, tract-level housing provision is inelastic in the Los Angeles region from 1990 to 2000. While Saiz (2010) finds the population-weighted housing supply elasticity in large U.S. is

25. The coefficients in columns 3–4 should be equal in magnitude and opposite in sign. They are not statistically different in absolute value (Panel C). A heteroskedasticity- and weak instrument-robust bootstrap 95% confidence interval is [1.008, 3.672] with a median value of 1.608 for the results in column 6; see Section 8 and Appendix D for details.

1.75, the estimate for the Los Angeles area is 0.63, which is very close to the results in columns 3–6 of Table 5.

7 Non-commuting effects of transit

Given parameters $\{\epsilon, \psi, \alpha, \zeta\}$ and data on workplace wages, residential housing prices, and commuting, the model delivers straightforward expressions to recover local economic fundamentals—they are the model residuals $\{\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{E}\}$.[26] These economic fundamentals represent economic characteristics of a place that exist outside of a market equilibrium. In combination with market forces, fundamentals determine equilibrium prices and the distribution of people.

Because these residuals embed information on local fundamentals, they can be used to study the effects of policy. Consider a local intervention, T. In general, the intervention could impact any local fundamental. The following econometric framework permits estimating the effect of the intervention on local fundamentals:

$$\hat{\mathbf{Y}}_{it} = \boldsymbol{\lambda} T_{it} + \varsigma_i + \varepsilon_{it} \tag{15}$$

where $\boldsymbol{\lambda} = \{\lambda^A, \lambda^B, \lambda^C, \lambda^E\}$ are the effects to be estimated and $\hat{\mathbf{Y}} = \{\widehat{\mathbf{a}}, \widehat{\mathbf{b}}, \widehat{\mathbf{c}}, \widehat{\mathbf{e}}\}$ are the logged (non-commuting) fundamentals (Section 8 shows how to combine the commuting and non-commuting effects for counterfactual estimation). Standard research designs can be used to identify $\boldsymbol{\lambda}$. While the full sample should be used to estimate the structural elasticities, the effects of interventions may use a different sample.

7.1 The effects of the LA Metro on non-commuting fundamentals

I now test whether transit shifts non-commuting fundamentals using Equation (15). For single-tract (rather than tract-pair) analysis, define:

$$\text{Proximity}_i^{\bar{d}} = \frac{\max\{0, \bar{d} - \min_k\{\text{dist}_i(\text{MetroStation}_k)\}\}}{\bar{d}} \in [0, 1],$$

where k indexes stations and $\bar{d}$ is some maximum distance (either 500m or 1km). This normalizes proximity so that it equals one when a tract contains a station, and zero if a tract is more than $\bar{d}$ from a station. I reuse the History & Shocks designs to identify λ^A and λ^B in a difference-in-difference design.[27]

26. I assume $\zeta = 0.65$, implying that the household expenditure share on housing is $1 - \zeta = 0.35$ and that the elasticity of housing demand is $-\epsilon(1-\zeta) = -0.76$. I assume that labor's share in production is $\alpha = 0.68$. These parameters are not quantitatively import for welfare, but matter for correctly recovering local fundamentals. Note that while $\mathbf{D}$ can be thought of as a residual, λ^D can be recovered as in Section 4.

27. I assume that $\lambda^C = \lambda^E = 0$ as it is unlikely that transit itself can shift either of these margins. Appendix Table H9 tests these asumptions.

Data limitations prohibit pre-trend analysis in fundamentals prior to 1990. However, recall the pre-trend comparisons in Section 4 (see Appendix Table H1). The Immediate 1925 Plan sample does not exhibit differential pre-trends across model-relevant variables. However, because there are some pre-trends in other variables, I include the 1990 levels of sociodemographic variables (income, education, and manufacturing employment) to allow for differential trends according to initial conditions.

While Section 4 shows strong evidence that LA Metro Rail increases commuting between connected locations, I find little evidence of a large effect on other margins. Table 6 reports the estimated effect of changes in transit proximity between 1990 and 2000 on tract-level productivity (panels I and II) and residential amenities (panels III and IV). I assume exogenous fundamentals in panels I and III, but also show results from a model extension with endogenous agglomeration in panels II and IV (see Appendix D.2). Results are similar across different values of $\bar{d}$, different research designs, and whether or not endogenous agglomeration effects are accounted for. The one exception is that, in the PER sample, there is some evidence of a positive residential amenity effect. However, it is countered by smaller and insignificant estimates in other samples.

These results are perhaps surprising, as these margins have been the subject of considerable research. Chatman and Noland (2014) and Duranton and Turner (2012) find evidence that transit increases city-level productivity and employment growth, while Kahn (2007) and Billings (2011) show some gentrifying effects of transit and that transit can anchor local development. Table 6 indicates that Los Angeles' does not mirror such experience (at least by 2000) and is consistent with Schuetz (2015), who does not find that new rail transit stations generally increase consumption amenities in California between 1992 and 2009.

There are two important caveats to the results in Table 6. These results only apply to LA Metro between 1990 and 2000; I cannot extend the non-commuting analysis to more recent years (I do expand the commuting analysis in Section 9). The network was limited in size and connectivity at this time. As the transit network has expanded, responses that depend on scale—or are slow—could manifest in more recent years. Second, the estimates in Table 6, while generally insignificant, are not precisely estimated zeros. For example, the productivity estimates are all between about 0.03 and 0.05 log points. Their insignificance does not preclude small positive effects.

Model robustness: Sorting and land use

Transit users may differ from those who do not use transit (Glaeser, Kahn, and Rappaport 2008; LeRoy and Sonstelie 1983). If so, transit could induce equilibrium sorting. However, I generally find little evidence of divergence in median household income between treated and control census tracts (see Appendix Table H10), though one specification shows a marginally significant decline. But Figure 4 shows the relationship between transit and rail usage by income centiles in 1990 and 2000, and reveals no relationship between income and rail usage for most of the income distribution.

The model assumes predetermined land use. While identification is robust to this assumption, counterfactual simulation may not be. I use zoning maps to test this channel and find little evidence of association between land use change and treatment. Table H10 indicates the change in residential land use is very small is very small in the full sample, but is a precisely estimated zero in preferred specification. This is perhaps unsurprising given strict zoning and land use regulation in the LA region (e.g., Quigley and Raphael 2005).

8 Welfare calculations

I use the model, estimated and selected parameters, and treatment status to estimate counterfactuals and calculate welfare changes. I employ hat notation (Dekle, Eaton, and Kortum 2008), letting $\hat{X}_{it} = X'_{it}/X_{it}$ represent the relative change of X to its counterfactual value X'. An iterative algorithm recovers counterfactual endogenous vectors $\{\hat{\mathbf{W}}, \hat{\mathbf{Q}}\}_{\forall i}$, $\{\hat{\boldsymbol{\pi}}\}_{\forall ij \in \mathcal{C}^+}$ (where $\mathcal{C}^+$ is the set of ij pairs with positive flows) relative to their observed values in 2000 (see Appendix C for details). Alternative scenarios are generally defined by adjusting fundamentals so that $\hat{X}_{i(j)} = \exp(-\lambda^X T_{i(j)})$, for $X \in \{A, B, C, D, E\}$. In the scenarios I consider below, I maintain the assumption that $\lambda^C = \lambda^E = 0$ and enforce the insignificance of other variables.[28]

The assumption of an open or closed city plays an important role. In a closed city, total population does not adjust. This means that there are real utility gains; these gains are equalized across the city through general equilibrium movements in prices. The model delivers a simple expression for welfare changes as a function of changes in local fundamentals and prices—a hat-notation variant of Equation (5):

$$\%\Delta \text{ Welfare } \approx \ln \hat{\bar{U}} = \frac{1}{\epsilon} \ln \left(\frac{\hat{B}_i \hat{E}_j \hat{D}_{ij} \hat{W}_j^{*\epsilon} \hat{Q}_i^{*-\epsilon(1-\zeta)}}{\hat{\pi}_{ij}^*} \right) \tag{16}$$

for each ij, where $\hat{X}^*$ indicates the equilibrium value of X in the counterfactual under autarky (that is, fixing $\hat{\bar{N}} = 1$). Because utility is homogeneous of degree one in wage, a proportional change in utility is equivalent to a proportional change in wage. To convert this to levels, I multiply the proportional change in utility by the average annual wage ($31,563) and aggregate population of workers (6.73 million) in 2000.

Instead, if the city is open, its total population $\hat{\bar{N}}$ also adjusts so that the expected utility in the city remains $\bar{U}$. Thus aggregate welfare for incumbent residents is unchanged. Because no spatial arbitrage means $\bar{U}$ in an open city is unchanged in response to changes in fundamentals, I instead report changes in total population.

28. That is, $\lambda^A = \lambda^B = 0$ from Table 6, and the third element of λ^D corresponding to proximity iii) is also 0 (from Table 2). Appendix Table H12 experiments with other λ^A and λ^B and reduced land use regulation.

Annualized costs combine two elements: (i) operating subsidies and (ii) annualized capital expenditures. The annual operating subsidy for the rail portion of LA Metro's operations for FY 2001-2002 is about \$162 million (2016 dollars). Total system cost for lines and stations completed by 1999 is \$8.7 billion (2016 dollars). I provide several annualizations of capital expenses. LA Metro's borrowing terms at the time were about 6%, so the annual payment for a 30-year loan is roughly \$635 million. However, subways last for a long time, so it may be appropriate to use a lower social discount rate. With a discount rate of 2.5% over an infinite horizon, capital expenditures are \$218 million per year. Combining with the operating subsidy yields an annualized cost between \$380 million and \$797 million per year.

Welfare effects by 2000

Table 7 reports the changes in aggregate welfare and population due to LA Metro Rail. Panels A and B report baseline parameter values and estimates, respectively (column 1), as well as bootstrap values (columns 2–3). The bootstrap procedure is non-standard to preserve the correlation structure across $\{\epsilon, \psi, \lambda^{D'}\}$, which are themselves estimates from IV and dyadic models. Standard resampling techniques are often overly conservative for both IV and dyadic estimators (Davidson and MacKinnon 2010; Davezies, D'Haultfœuille, and Guyonvarch 2019). I design a system wild bootstrap technique that bridges the wild restricted efficient residual bootstrap of Davidson and MacKinnon (2010) and the double-difference bootstrap of Menzel (2020); see Appendix E.3 for details.

LA Metro Rail by 2000 generates an annual baseline benefit of \$93.6 million in 2016 USD (a 0.044% increase in welfare). In an open economy, the employed population of the Los Angeles region is 0.088% higher with LA Metro Rail. The 95% bootstrap confidence interval is [\$11.9 million, \$380.5 million] (an increase of welfare between 0.006% and 0.179%). The baseline commuting benefit of LA Metro Rail by 2000 is about 16% of an annualized cost of \$597 million; the baseline benefit most likely lies between 2% and 64% of this annualized cost. Under the lowest assumption of the annualized costs, the baseline benefit is 25% of cost (confidence interval from 3% to 100%) by 2000. Under the highest assumption, the baseline benefit is 12% of cost (confidence interval from 1% to 48%) by 2000.

A general conclusion across baseline specifications is that the commuting benefit of rail transit in Los Angeles does not exceed its cost by 2000. Regardless of the discount rate, baseline benefits are a bit more than half of the operating subsidy of \$162 million. However, the baseline commuting benefits do not cover the capital expenses at standard discount rates.

9 Extensions and Discussion

Longer-run Commuting Effects under Habituation. Because LA Metro Rail was still relatively new in 2000, I extend the commuting analysis to determine if there are additional effects of transit on commuting flows in more recent years. I use data from the 2002 and 2015 LEHD Origin-Destination Employment Statistics (LODES). Because LA Metro Rail expanded during this period, I estimate a variant of Equation (2) on the LODES panel with two different effects: (i) *New Transit* for the effect of new stations (built after 2002) on bilateral flows, and (ii) *Existing Transit* for the additional increase between tracts connected by stations built earlier (between 1990 and 2002).

Results in Table 8 indicate that new transit connections increase commuting by 10%–14% between tract pairs that both contain stations by 2015. For tract pairs slightly farther away, the may be up to 9%, but is insignificant in the full and PER samples. While substantial, these effects are likely smaller than the effects of connections between 1990 and 2000 because stations built between 2002 and 2015 generally connect more suburban locations. Tract pairs that had been previously connected by transit (before 2000) experience additional commuting growth by 2015: Pairs both containing a station show another 8%–12% increase in commuting, and tract pairs a bit further away show an additional 5%–10% growth. This is evidence that (i) aggregate commuting flows take decades to adjust to new transit modes (i.e., *habituation*), and/or (ii) there are increasing returns in transit network size.

A significant omission of the 1990-2000 welfare analysis in Section 8 is the exclusion of these later benefits. There are two cases to consider: (1) If increased commuting is due to habituation, the full commuting increase between previously connected stations is attributable to early system construction; (2) if, however, there are increasing returns in network size, increased commuting between existing stations is due to new stations and lines. These two cases bound the commuting benefit over a 25-year horizon for the system constructed before 2000 (and thus using the same cost basis). The upper bound is given by (1); additional benefits form the *Existing Transit* add to those before 2000. As a lower bound, in case (2) the additional benefit is zero .

Assuming habituation, I combine the effects from Table 2 and the *Existing Station* effects from Table 8 and simulate the new outcome. Accounting for these additional effects, the initial portion of LA Metro Rail constructed by 2000 generates up to \$169.2 million annually by 2015 (an increase of \$75.6 million over the baseline). Unfortunately, data limitations prevent testing for longer-run effects of transit on non-commuting margins.

Congestion. As discussed in Section 4.3, there may be no long-run effect of increased transit capacity on road congestion. However, Table 3 suggests measurable congestion benefits persist several years after transit lines open. I can incorporate these transit-induced time savings into the welfare calculation, implicitly presuming that they last in perpetuity. To do so, the model requires a measure of the elasticity of commuting with respect to travel time. I estimate a value of -0.239

from a two-step gravity-based procedure (see Appendix F).

The total benefit of LA Metro Rail accounting for decreased congestion from transit is $225.9 million annually by 2000 (an increase of $132.3 million from baseline). This exceeds annual operating costs, though it only exceeds total costs under a very low discount rate. This result is substantially smaller that the long-run estimates in Anderson (2014) of $1-$2 billion annually.[29]

Air Pollution. Relatedly, decreased air pollution from decreased congestion may provide an additional benefit. Gendron-Carrier et al. (2021) show that, among global cities with above average pollution, subways lead to a mild decrease in air pollution. Applying their estimates to to Los Angeles County, LA Metro Rail by 2000 would have led to reductions in air pollution corresponding to 50.4 fewer infant deaths annually. As the medium-run results travel-time savings in Table 3 are roughly one-third of those in Anderson (2014), I take one-third of the potential avoided infant deaths as a baseline long-run estimate of 16.8 fewer infant deaths. Assuming a standard value of statistical life of $6 million, this generates $101 million annually in additional benefits.

There are several important caveats to this back-of-the-envelope calculation. First, it excludes other health benefits from reduced air pollution, such as reduced mortality of non-infants and reduced morbidity of the population overall. Second, as with congestion, reductions in pollution may well be transitory. Third, this treats Los Angeles as a high-pollution city, whereas its pollution levels are lower than many of those in Gendron-Carrier et al. (2021). Finally, these results assume that the benefit of LA Metro Rail is distributed evenly throughout Los Angeles County, regardless of proximity to LA Metro Rail.

Agglomeration. Incorporating agglomeration changes welfare little, because the relative effects of LA Metro Rail in any one location are not large. There are two margins to consider: At the metropolitan level, suppose a simple agglomerative force increases productivity by 5% everywhere for each doubling of city population (Ciccone and Hall 1996). Welfare is homogeneous of degree one in wage, and wage is proportional to productivity, so productivity in an open city increases by $\ln(1 + 0.05 \times 0.00088) \approx 0.0044\%$, about $9 million annually. The other margin is local agglomeration. Including these forces as implemented in Ahlfeldt et al. (2015) slightly decreases the welfare generated by LA Metro Rail (to $91.8 million), indicating that LA Metro Rail slightly decentralizes population.

9.1 Discussion

Baseline estimates of the benefit of LA Metro Rail solely reflects non-congestion commuting benefits of roughly $100 million per year. Various extensions increase the benefit of LA Metro Rial by up

29. Anderson (2014)'s approach is based on the value of travel time saved, whereas my approach relies on revealed preference. However, some caution should be implied in interpreting both sets of results, as neither model fully endogenizes congestion; see Brinkman (2016) and Allen and Arkolakis (2019) for endogenous congestion.

to \$200 million annually, broadly in line with the lower end of annualized costs. Some particular characteristics of LA Metro Rail and Los Angeles warrant note when discussing broader conclusions, especially targeting and disperse commuting patterns, zoning, costs, and federal funding.

LA Metro Rail does not connect the residences and workplaces of many commuters. Only between 1%–3% of the 1990 population of Los Angeles County both lived and worked in tract pairs near rail stations by 2000 (Table 1). Figure 5 plots the likelihood of becoming treated by ex ante (1990) flows for pairs ij with $i \neq j$ in the Immediate 1925 Plan sample. While the positive relationship indicates that transit was placed often where it could have a larger absolute effect, many high-flow pairs are not connected. Linking denser corridors (such as Wilshire Boulevard) would have generated greater gains. Regardless, Los Angeles has a polycentric distribution of jobs and residences (Redfearn 2007) that is less amenable to transit adoption. Indeed, residing close to a transit station increases the likelihood of using LA Metro Rail by only 0.8 percentage points without conditioning on workplace on a base of zero (Appendix Table H11).[30]

Land use regulations also inhibited the ability of locations receiving stations to adjust building stock. Essentially no land was converted to residential use near LA Metro Rail stations (Appendix Table H10). Relatedly, Proposition U, passed in 1986, halved allowable density throughout much of Los Angeles just before LA Metro Rail opened. Such legislation combined with political constraints meant the "coordinated land use and rail planning ... died a gory death" (Elkind 2014, p. 71). Generally, land use policies interact with transportation choice. In cities with automobile-friendly land use policies, many factors can limit transit adoption even if transit is well-supplied (Bunten and Rolheiser 2020; Schuetz, Giuliano, and Shin 2018). Restrictive zoning may have slowed adjustment to and adoption of LA Metro Rail, and longer-run analysis may well find larger effects. Indeed, if land use regulations had eased up to permit 10% higher residential density in census tracts that contained transit stations, LA Metro Rail's effect would have been 44%–140% larger without much (or any) additional expense (see Appendix Table H12).

Third, while I take as given the costs of LA Metro Rail, lowering the capital and operating costs of transit would certainly aid cost-benefit calculations. There is a growing body of evidence that infrastructure in the United States is much costlier than elsewhere in the world and that these costs have been increasing over time (Brooks and Liscow 2019; Levy 2016; Mehrotra, Turner, and Uribe 2019). While there is not yet a clear consensus on the causes of or solutions to these differences, if the costs of LA Metro Rail were, for example, half of their observed levels, estimated benefits would meet or exceed costs.

Finally, capital expenditures on transit are largely funded with federal dollars in the U.S.,

30. In comparison, consider that Tsivanidis (2018) finds that Bus Rapid Transit (BRT) in Bogotá increases welfare roughly 40 times larger than the baseline effect of LA Metro Rail. Comparing commuter behavior across the two cities suggests that the difference is due to comparatively low adoption of rail (and transit more generally) in Los Angeles. Before Bogotá's BRT was built, 73% of commuters took the bus; afterwards, the BRT had 2.2 million trips per day and 36% of commuters used it. In contrast, in Los Angeles before Metro Rail, 5%–7% of commuters took the bus; by 2000, just 0.4% of commuters used the subway and there were about 120,000 trips per day.

with states and localities making up the difference. From 1996 and 1999, between 26%–45% of LACMTA's capital expenditures were funded with local dollars. It is therefore possible for a benefit-cost calculation considering only local costs to be positive, which could be the relevant decision margin for local decision makers.

There are margins to which this paper does not speak. City-wide effects are difficult to measure with this approach. Nor can I directly speak to benefits resulting in better transit provision for non-commuting trips (though this margin could show up as a residential amenity, which I do not find). This framework does not capture the benefits for non-workers. Such effects are particularly important for equity concerns and are unfortunately understudied. Relatedly, the assumption of homothetic preferences may limit my ability to measure more sizable utility gains for populations with greater transportation cost sensitivity.

10 Conclusion

This paper develops a method for evaluating the benefits of transit from commuting flow data, estimates an equilibrium model of a city with costly commuting, and uses the model to estimate the impact of Los Angeles Metro Rail on welfare. The model is sufficiently parsimonious to permit transparent identification and estimation. The elasticity of labor supply plays a key role governing homogeneity in location preference, and its small estimated value indicates agents are relatively unwilling to relocate and are not very responsive to changes in local conditions or policies. Conversely, this implies that observed responses to transit correspond to significant utility gains.

I provide new insights into how transit influences city structure by isolating the commuting benefit of transit from other margins. LA Metro Rail increases commuting between the census tracts nearest to stations by 16% in the first decade after construction, relative to control groups selected by proposed and historical transit routes. Nearby locations also experience increases of up to 14%. There is some evidence that Metro Rail reduces congestion in the medium-run.

Baseline welfare estimates show positive annual benefits of LA Metro Rail to be $94 million by 2000. These welfare benefits are smaller than the operational and capital costs of LA Metro's light rail and subway lines. I also provide evidence of dynamic effects that indicate the long-run benefits of LA Metro Rail's 2000 network may be up to $169 million per year. While these welfare estimates leave out some other benefits of transit (such as benefits for non-workers), results warrant a note of caution to cities—and particularly polycentric, automobile-oriented cities—expecting rail investment to lead to large increases in overall welfare within 10 to 25 years, relative to its cost.

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Figure 1: Map of Proposed LA Metro Lines and PER Lines in Kelker, De Leuw & Co. (1925)

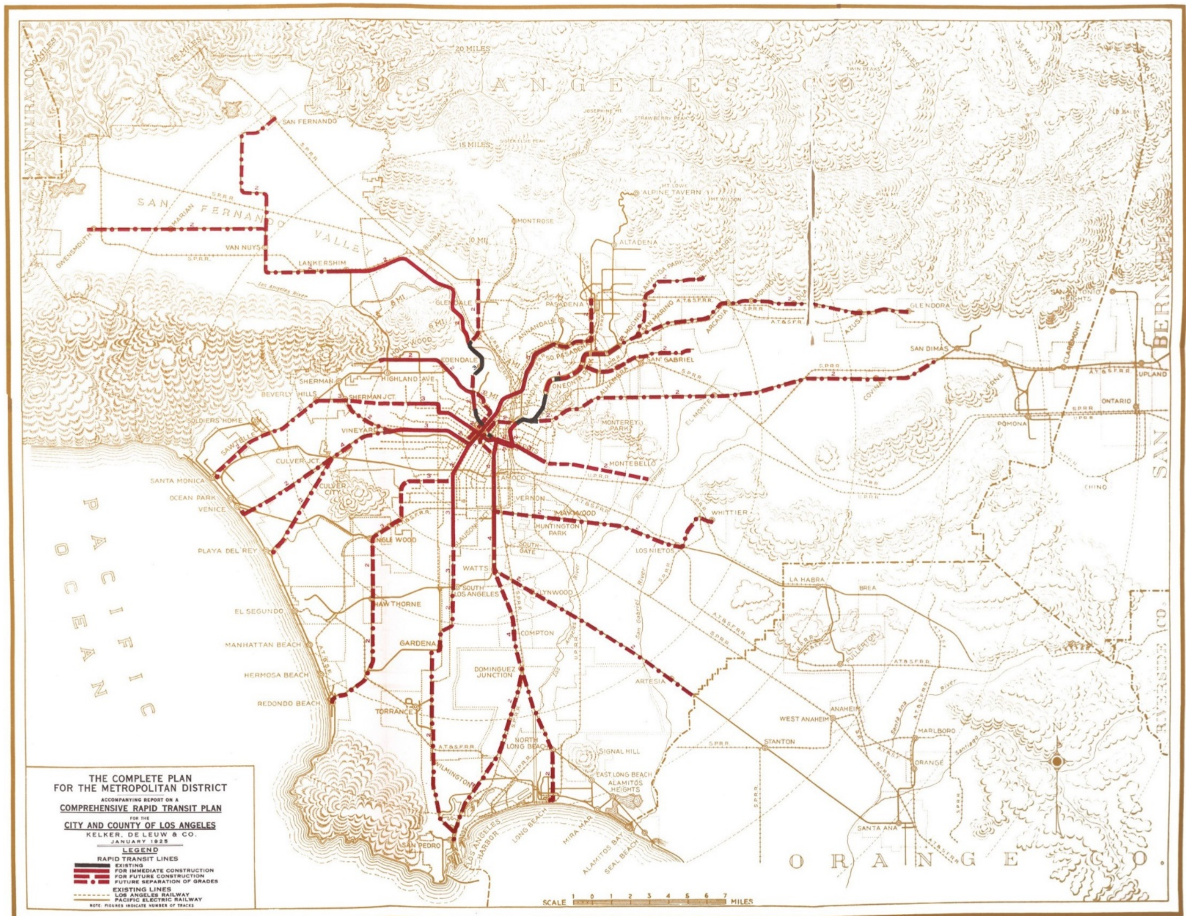


PLATE NO. 1

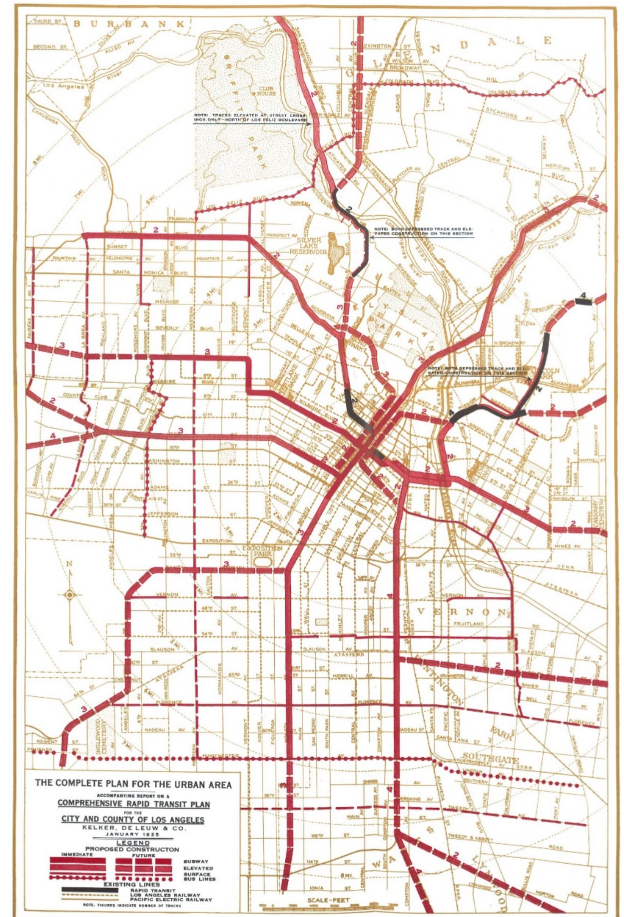
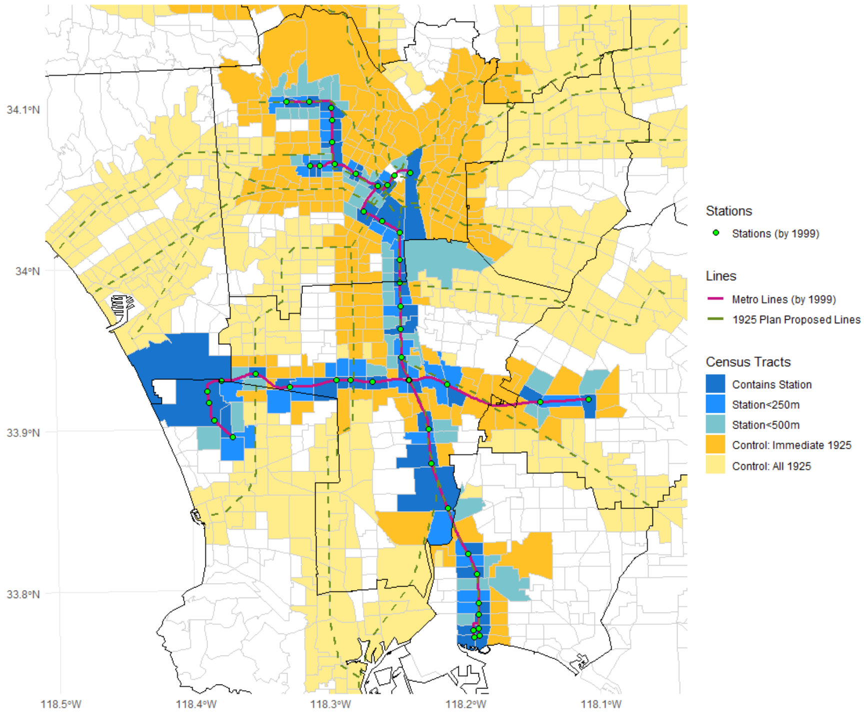


PLATE NO. 2

Figure 2: Map of LA Metro lines, stations, and the 1925 Plan and PER Lines

(a) 1925 Plan Sample



(b) PER Lines Sample

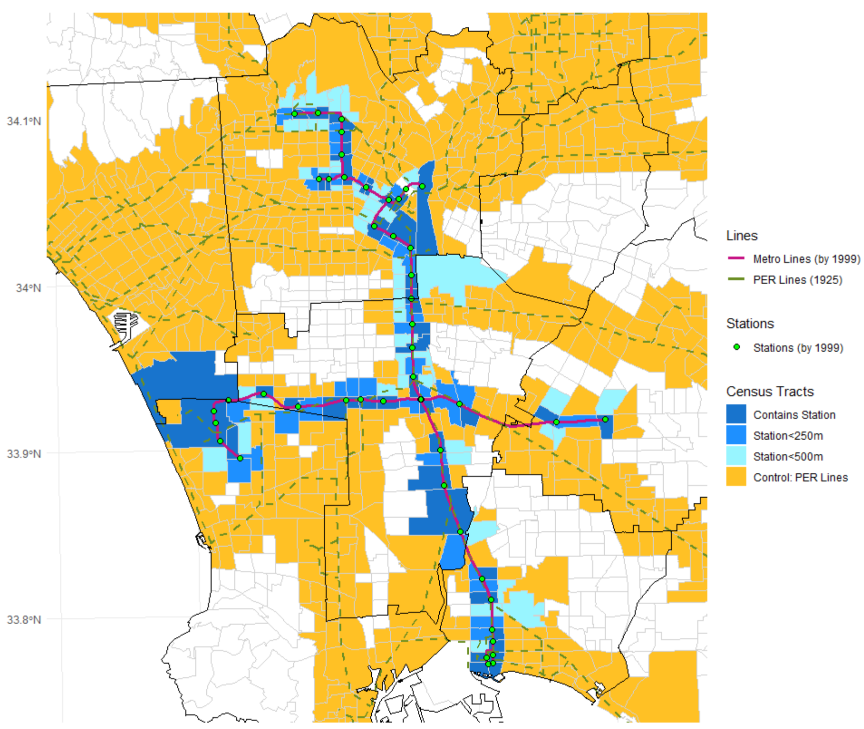


Figure 3: Does $\omega = \epsilon w$, and if not, what is it capturing?

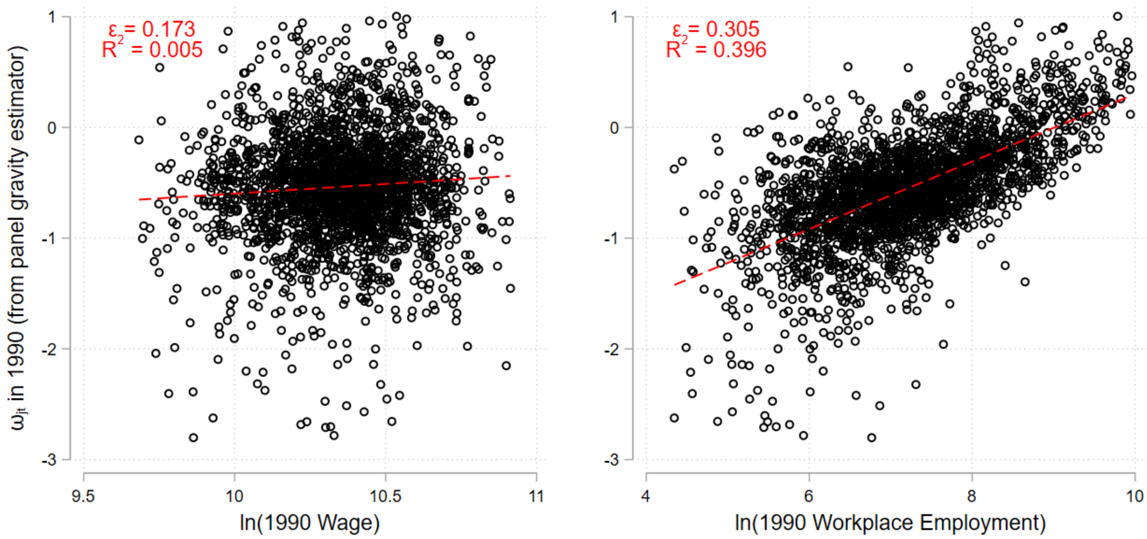


Figure 4: Take-up of LA Metro Rail for Los Angeles County commuters does not vary by income, but overall take-up of transit (including bus) does.

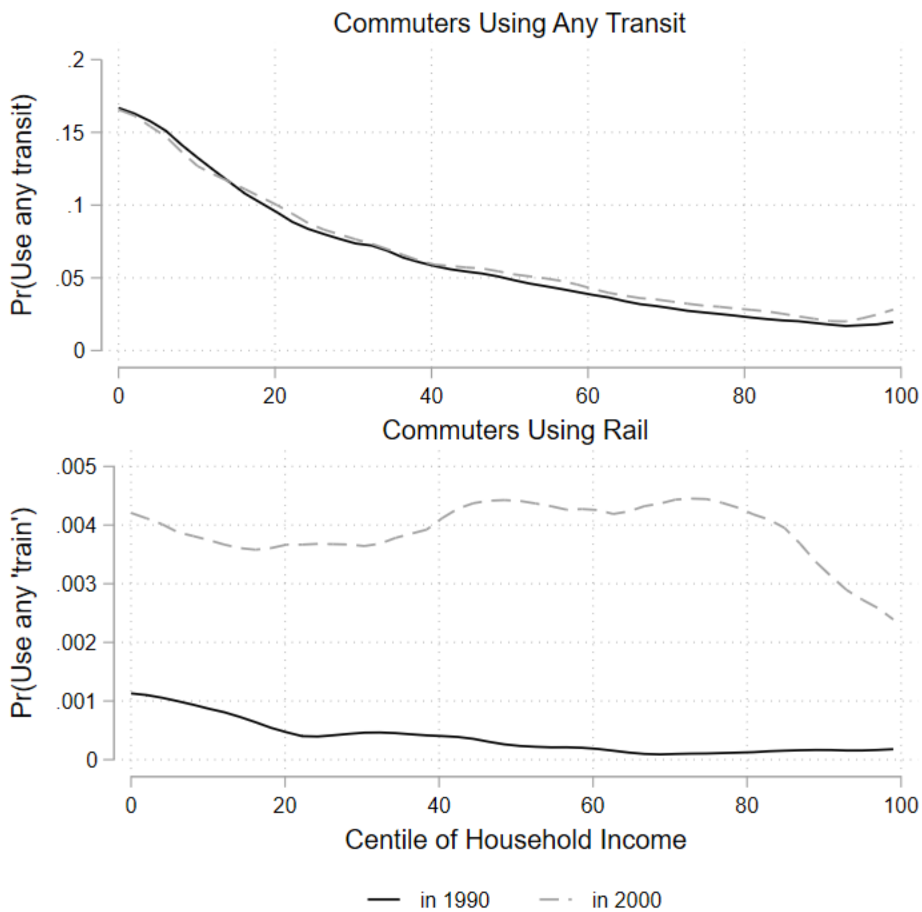


Figure 5: Tract pairs with higher ex-ante commuting flows are a bit more likely to receive LA Metro Rail by 2000, but many high commuting pairs do not.

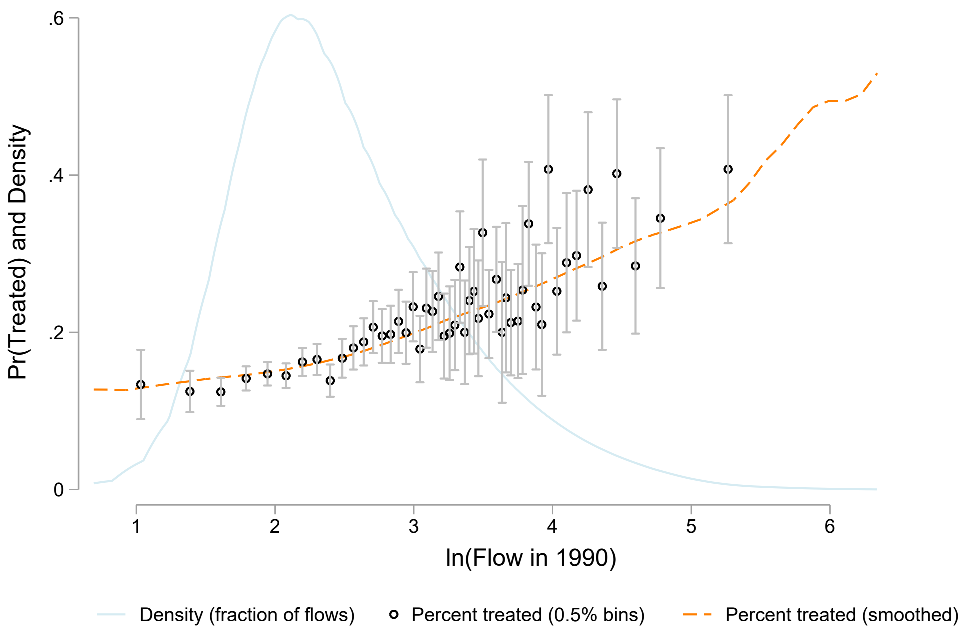


Table 1: Descriptive statistics on transportation in Los Angeles and station placement

	LA County		Full Sample	
	(1)	(2)	(3)	(4)
A. Pre-treatment mode choice characteristics (1990)				
% workers commuting via: Drive alone	71.8%		74.5%	
% workers commuting via: Carpool	15.8%		15.8%	
% workers commuting via: Bus	6.9%		4.6%	
B. Commuting characteristics				
Commute time (minutes, 1990)	26.3 [16.8]			
Commute time (minutes, 2000)	28.0 [18.3]			
C. % of pre-treatment population that becomes treated	Centroid $< 500m$	Any $< 500m$	Centroid $< 500m$	Any $< 500m$
% workers at POW tract that receive treatment	11.3%	19.4%	7.2%	12.3%
% workers at RES tract that receive treatment	2.6%	8.1%	1.6%	4.8%
% workers that receive transit connection RES-POW	0.6%	2.9%	0.4%	1.7%

Data from Census micro records (from IPUMS) and 1990 CTPP. LA County restricts analysis to workers both living and residing in Los Angeles county, while the full sample includes all five counties in the main sample. Brackets indicate standard deviation. Commute times are weighted by flows.

Table 2: Effect of Transit on Commuting Flows by 2000 (Log-Linear with HDFEs)

	Full Sample			History & Shocks			Same Line	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
O & D contain station	0.100***	0.111***	0.100***	0.111**	0.145***	0.149**	0.157*	0.201**
	(0.038)	(0.038)	(0.038)	(0.044)	(0.045)	(0.061)	(0.089)	(0.093)
O & D <250m from station		0.076*	0.056	0.090*	0.104**	0.128**	0.051	0.061
		(0.046)	(0.047)	(0.051)	(0.051)	(0.065)	(0.075)	(0.079)
O & D <500m from station		0.001	-0.013	0.020	0.014	0.012	-0.032	0.070
		(0.037)	(0.036)	(0.040)	(0.042)	(0.053)	(0.067)	(0.067)
N	291532	291532	291110	99480	74408	19222	8280	4496
Control Group	All	All	All	PER	Full '25 Plan	Immed. '25 Plan	Ever Treated	Treated by 2000
Standard Three-Way FEs	Y	Y	Y	Y	Y	Y	Y	Y
Subcounty Pair-×-Year FEs	-	-	Y	Y	Y	Y	Y	Y
Highway Controls	-	-	Y	Y	Y	Y	Y	Y

High-dimensional fixed effects estimates of λ^D with log-linear estimator; standard three-way fixed effects are tract of work-by-year, tract of residence-by-year, and tract pair. Outcome is log commuting flow. Treatment variables are mutually exclusive. Column titles refer to design: tracts pairs on any lines are treated in Columns (1)-(6), while only tract pairs on the same line are treated in Columns (7) and (8). Standard errors clustered by tract pair, tract of residence, and tract of work in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Does transit decrease congestion?

	$\ln(\text{Time}_{ijt}^{\text{All}})$		$\ln(\text{Time}_{ijt}^{\text{Car}})$	
	(1)	(2)	(3)	(4)
Share of route <250m from transit line	-0.079*	-0.020	-0.144*	-0.150*
	(0.043)	(0.042)	(0.084)	(0.085)
Share of route 250m-500m from transit line	-0.051	-0.023	-0.197**	-0.189**
	(0.062)	(0.063)	(0.089)	(0.093)
Share of route 500m-1km from transit line	-0.036	-0.016	0.011	-0.024
	(0.048)	(0.047)	(0.076)	(0.075)
Share of route 1km-2km from transit line	-0.039	-0.022	-0.052	-0.070
	(0.028)	(0.028)	(0.057)	(0.054)
Share of route 2km-4km from transit line	-0.006	0.012	0.013	0.002
	(0.019)	(0.019)	(0.032)	(0.035)
N	286392	286142	89614	89432
Control Group	All	All	All	All
Standard Three-Way FEs	Y	Y	Y	Y
Subcounty Pair-×-Year FEs	-	Y	-	Y
Transit Controls	Y	Y	Y	Y
Highway Controls	Y	Y	Y	Y

High-dimensional fixed effects estimates of the changes in the share of a route near transit on log travel time; standard three-way fixed effects are tract of work-by-year, tract of residence-by-year, and tract pair. Average reported travel time from the CTPP reflects all modes in Columns (1)-(2) and only automobiles in Columns (3)-(4). Times with implied speeds greater than 80mph are excluded. Treatment variables are mutually exclusive. Highway controls are shares of a route within 250m and 1km of the Century Freeway, and transit controls are the treatment variables in Table 2. Standard errors clustered by tract pair, tract of residence, and tract of work in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: IV estimates of labor supply elasticity (ϵ)

	$\Delta\hat{\omega}_{jt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
A. IV Estimates of ϵ						
$\Delta\ln(W_{jt})$	1.284*	0.807	2.904**	2.373**	2.512**	2.180*
	(0.698)	(0.693)	(1.221)	(1.206)	(1.094)	(1.171)
B. First Stage						
Δz_{jt}	1.150***	0.918***	1.165***	0.939***	1.165***	0.939***
	(0.332)	(0.333)	(0.331)	(0.332)	(0.331)	(0.332)
F-stat (CD)	48.2	27.9	50.8	29.8	50.8	29.8
F-stat (KP)	12.0	7.6	12.4	8.0	12.4	8.0
N	2432	2426	2533	2525	2533	2525
$\hat{\omega}$ estimated:	Linear, Panel		PPML Yr-by-Yr		PPML Panel	
Subcounty-$\times$-Year FEs	-	Y	-	Y	-	Y

Panel instrument variable (IV) estimates of regression of $\hat{\omega}_{jt}$ on w_{it}. Estimated in differences using wage instrument. CD and KP refer to the Cragg-Donald and Kleibergen-Paap tests, respectively. Weighted by 1990 workplace employment. Columns 1-2 use a log-linear panel specification to estimate ω_{jt}; columns 3-6 use PPML estimation (estimated year-by-year in columns 3-4 using distance as a gravity term and as a panel in columns 5-6 with ij fixed effects). Place of work-by-year fixed effects ($\hat{\omega}_{jt}$) estimated in the panel in columns 1 and 3 with ij fixed effects. Sample size reflects count of differenced observations. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: IV estimates of inverse housing supply elasticity (ψ)

	$\Delta q_{it} = \Delta \ln(Q_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
A. IV Estimates of ψ						
$\Delta \ln(\text{Density}_{it})$	2.325**	2.168***				
	(0.939)	(0.807)				
$\Delta \ln(\text{Hous. Cons.}_{it})$			1.762***	1.644***		
			(0.533)	(0.476)		
$\Delta \ln(\text{Res. Land}_{it})$			-2.082**	-1.927**		
			(0.970)	(0.945)		
$\Delta \ln(\text{Hous. Density}_{it})$					1.687***	1.602***
					(0.508)	(0.453)
B. Housing Supply Elasticity						
$1/\psi$	0.430**	0.461***	0.568***	0.608***	0.593***	0.624***
	(0.174)	(0.172)	(0.172)	(0.176)	(0.178)	(0.177)
C. Specification Test ($H_0 : \psi_{\text{Hous. Cons.}}/\psi_{\text{Res. Land}} = -1$)						
$\psi_{\text{Hous. Cons.}}/\psi_{\text{Res. Land}}$			-0.846	-0.853	-1	-1
$[\cdot] = \Pr(H_0)$			[0.590]	[0.616]		
D. First Stage						
$\Delta z_{it}^{HD(,a)}(\rho)$	-1.397***	-1.468***	-2.398***	-2.303***	-1.945***	-2.003***
	(0.525)	(0.504)	(0.711)	(0.721)	(0.588)	(0.571)
F-stat (CD)	5.5	6.1	9.6	10.7	10.9	11.5
F-stat (KP)	7.1	8.5	11.3	12.4	10.9	12.3
N	2232	2232	2175	2175	2175	2175
Empl. instrument	All	Not i	All	Not i	All	Not i

Panel instrument variable (IV) estimates of regression of median house value on population, housing consumption, and residential land, using $\ln(\rho) = -5.5$ and employment IV. CD and KP refer to the Cragg-Donald and Kleibergen-Paap tests, respectively. Housing prices excluded if either year is top-coded. Weighted by 1990 number of homeowners. Columns 2, 4, and 6 exclude own tract during instrument construction. Sample size reflects count of differenced observations. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Transit and non-commuting fundamentals (other effects of transit)

	$\Delta\hat{\mathbf{Y}}_{it}$ (Productivity and Amenities)							
	$\bar{d}$ = 500m				$\bar{d}$ = 1km			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Effect on productivity								
I.) λ^A estimated using $\Delta\hat{A}$								
Proximity$_i \times t$	0.033	0.029	0.016	0.020	0.041	0.040	0.026	0.034
	(0.039)	(0.039)	(0.039)	(0.043)	(0.037)	(0.038)	(0.037)	(0.043)
N	2509	1167	934	394	2509	1167	934	394
II.) λ^A estimated using $\Delta\hat{\mathcal{A}} = \Delta\hat{A} - \mu\Delta\ln(\Upsilon)$								
Proximity$_i \times t$	0.028	0.029	0.017	0.021	0.036	0.041	0.026	0.036
	(0.038)	(0.039)	(0.038)	(0.042)	(0.036)	(0.037)	(0.037)	(0.042)
N	2469	1167	934	394	2469	1167	934	394
Effect on residential amenity level								
III.) λ^B estimated using $\Delta\hat{B}$								
Proximity$_i \times t$	0.053	0.070**	0.047	0.008	0.038	0.057*	0.027	-0.027
	(0.033)	(0.034)	(0.034)	(0.036)	(0.029)	(0.032)	(0.031)	(0.035)
N	2160	994	815	343	2160	994	815	343
IV.) λ^B estimated using $\Delta\hat{\mathcal{B}} = \Delta\hat{B} - \eta\Delta\ln(\Omega)$								
Proximity$_i \times t$	0.049	0.066**	0.043	0.007	0.034	0.054*	0.023	-0.027
	(0.031)	(0.032)	(0.032)	(0.034)	(0.028)	(0.030)	(0.029)	(0.032)
N	2153	993	814	343	2153	993	814	343
Control Group	All	PER	Full '25 Plan	Immed. '25 Plan	All	PER	Full '25 Plan	Immed. '25 Plan

Results from thirty-two regressions of transit proximity on local fundamentals. Here, the distance effect of agglomeration decays at the values in Ahlfeldt et al. (2015). All regressions include tract fixed effects, subcounty-by-year fixed effects, and controls. Controls include changes in highway proximity and 1990 levels of log household income, share of residents with at least a high school degree, and manufacturing employment. Sample size reflects number of differenced tracts. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Welfare estimates in 2000 (in $2016)

	Preferred Estimate (1)	Bootstrapped Results: Median (2)	Bootstrapped Results: 95% CI (3)
A. Parameter Values			
ϵ	2.180	2.157	[0.562, 8.856]
ψ	1.602	1.608	[1.008, 3.672]
λ^D, O & D contain station	0.149	0.136	[0.016, 0.257]
λ^D, O & D <250m from station	0.128	0.117	[0.022, 0.211]
B. Bootstrapped Welfare Change (Primary Model)			
Closed Economy			
Annual Δ in welfare	0.044%	0.040%	[0.006%, 0.179%]
(in $2016)	**$93.6 mil.**	$85.1 mil.	**[$11.9 mil., $380.5 mil.]**
Open Economy			
Population Δ	0.088%	0.081%	[0.008%, 0.348%]
C. Extensions ($2016)	Total		Addition to $93.6 mil.
Congestion†	$225.9 mil.		$132.3 mil.
Network Effects through 2015†	$169.2 mil.		$75.6 mil.
Agglomeration	$91.9 mil.		-$1.7 mil.
Air Pollution Mortality	$194.4 mil.		$100.8 mil
D. Annualized Cost ($2016)			
Capital Costs			
At 6% over 30 years	-$635 mil.		
At 5% over 50 years	-$479 mil.		
At 5% in perpetuity	-$435 mil.		
At 2.5% in perpetuity	-$218 mil.		
Operational subsidy in 2002	-$162 mil.		
Total Cost	**-$380 to -$797 mil.**		

Op. subsidy refers to the annual operation subsidy. Other parameters are $\zeta = 0.65$, $\alpha = 0.68$, $\epsilon\kappa = -0.239$, and λ^D as reported in column 6 of Table 2 (with the coefficient corresponding to distance iii) set to 0). Bootstrap results reflect 400 wild bootstrap draws. See text and appendices for details. †indicates an upper bound on the effect.

Table 8: Dynamic effects of transit on flows (2002-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
O & D contain *New* station	0.108***	0.110***	0.094***	0.105***	0.112***	0.133***
	(0.034)	(0.034)	(0.032)	(0.033)	(0.031)	(0.036)
O & D <250m from *New* station	0.038	0.038	0.022	0.035	0.046**	0.083***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.027)
O & D <500m from *New* station	0.032	0.031	0.017	0.035*	0.025	0.045*
	(0.022)	(0.023)	(0.021)	(0.020)	(0.020)	(0.025)
O & D contain *Existing* station		0.091**	0.084**	0.099***	0.098***	0.112***
		(0.038)	(0.036)	(0.034)	(0.032)	(0.030)
O & D <250m from *Existing* station		0.049*	0.048*	0.059*	0.061*	0.091***
		(0.027)	(0.029)	(0.032)	(0.035)	(0.029)
O & D <500m from *Existing* station	0.056**	0.048*	0.043*	0.041	0.028	0.032
	(0.022)	(0.025)	(0.025)	(0.025)	(0.025)	(0.029)
N	1993198	1993198	1992702	514082	385278	105794
Control Group	All	All	All	PER	Full '25 Plan	Immed. '25 Plan
Standard Three-Way FEs	Y	Y	Y	Y	Y	Y
Subcounty Pair-×-Year FEs	-	-	Y	Y	Y	Y

High-dimensional fixed effects estimates of λ^D with log-linear estimator; standard three-way fixed effects are tract of work-by-year, tract of residence-by-year, and tract pair. Outcome is log commuting flow. Treatment variables are mutually exclusive. Geography are 2010-vintage census tracts. Standard errors clustered by tract pair, tract of residence, and tract of work in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For Online Publication

Appendices and Supplemental Results

to accompany

Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification

by

Christopher Severen

February 2021

A Discussion of Data

In this Appendix section, I discuss all the sources of data that this project draws from and details relevant to sample construction. I pay particular attention to normalization. I also compare the CTPP and LEHD LODES data sources, and explain why they are not suitable to be used together.

A.1 Sources

- Census Transportation Planning Project (CTPP)
  - 1990 Urban Part II: Place of Work, Census Tract
  - 1990 Urban Part III: Journey-to-Work, Census Tract
  - 2000 Part 2
  - 2000 Part 3
- National Historical Geographic Information System (NHGIS)
  - Shapefiles, Block Group and Census Tract, 1990, 2000, and 2010
  - Census, Block Group and Census Tract aggregates, 1990 and 2000
- Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES)
  - Aggregated to tract-to-tract flows, 2002 and 2015, using constant 2010 geographies
- Geolytics Neighborhood Change Database (NCDB)
  - Census aggregates in constant 2010 geographies from 1970-2000
- Los Angeles County Metropolitan Transportation Authority (LACMTA)
  - Shapefiles of LA Metro stations and lines
  - Opening dates for stations and lines
  - Ridership data
  - Kelker, De Leuw & Company (1925). I georeference this map in ArcGIS, and then process it in R to provide geographic data to delineate the 1925 Plan and PER Line samples.
- IPUMS USA
  - Microdata on employment, wage, and industry by MSA for all non-CA residents, 1980-2000.
  - Microdata on transit in the 1990 and 2000 Censuses for LA area residents.
- Southern California Association of Governments
  - Land use and zoning maps: 1990, 1993, 2001, 2005.
- National Highway Planning Network

  - Shapefiles for the Century Freeway (I-105)

- Dynamap Road Network (Tele Atlas)
  - Calculate travel times using ArcGIS

- HERE API
  - Calculate travel times using HERE API, interfaced via HereR package in R

- Graphhopper routing engine and OpenStreetMap data
  - Develop shapefiles for fastest driving routes between tracts, and intersect with buffers around LA Metro Rail lines to determine route exposure transit.

A.2 Data construction details

Geographic normalization

Through my primary analysis (all results from 1990 and 2000, excluding the check on pre-trends), the unit of observation is the census tract according to 1990 Census geographies. The Transportation Analysis Zones used in Southern California in the 1990 CTPP are equivalent to census tracts from the 1990 Census that have been subdivided by municipal boundaries if they overlay multiple jurisdictions. I merge TAZs in 1990 that cross municipal boundaries and assign them to the corresponding census tract. Data from the 2000 CTPP and 2000 Census are both in 2000 geographies. I therefore overlay shapefiles delineating 2000 geographies on 1990 census tracts to develop a crosswalk that translates 2000 data into 1990 geographies.[F.1] Where possible, I use 2000 block group data and shapefiles to refine the crosswalk. More precisely, to create the crosswalk, I intersect the 2000 census tracts and census block group files with 1990 census tracts, and then clean to provide a set of weights to be used in converting 2000 data to the 1990 geographies. Note that the intersection method varies according to whether summation or averaging is desired. If summing, weights are the portion of a 2000 geography that overlays the 1990 census tract. If averaging, weights are the portion of the 1990 census tract that is covered by a 2000 geography. In all cases, I excluded intersected values that cover less than 0.5% of the targeted area to reduce noise (P1).[F.2]

To normalize 2000 flows and travel times to 1990 geographies, the crosswalk is merged twice into the data, once by origin and once by destination (using the Stata command joinby to ensure all combinations were made). I then collapse these data by 1990 origin-destination pairs, taking the raw sum areal weights as the 1990 flow counts and using the areal weights to determine travel times. Many travel times are not disclosed in the 2000 data, and are treated as missing and are ignored. The 2000 CTPP data do not report actual counts, instead rounding to the nearest 5 (except for 1-7, which is labeled 4). In order to treat 1990 and 2000 data similarly, I develop two approaches that are conservative, though they throw away potentially useful variation. Both are similar, but differ in how they treat small numbers. In approach (P2a), I divide flows by 5, and round to the

F.1. This is essentially the reverse process of the Longitudinal Tract Data Base in Logan, Xu, and Stults (2014); I bring current data to 1990 geographies because merging tracts induces less error than (perhaps incorrectly) splitting tracts.

F.2. There are constant small realignments of census blocks (which aggregate to tracts) to account for roads, construction, lot mergers, etc. I choose the 0.5% threshold because it is unlikely that this represented a substantive change in the census tract, but rather just a minor border adjustment.

nearest digit. In approach (P2b), I change any flow values between 1 and 4 inclusive to be 4, and divide by 5 and round to the nearest digit. Small digits are different in the two years: In 1990, digits <4 have actual meaning, whereas in 2000 digits <4 can only have been created through the areal weighting process. Both approaches accommodate these differences in a different way, and offer different truncation points (2.5 for approach (a), and 1 for approach (b)). Approach (b) is my preferred specification. For all flows-by-mode, I follow approach (b), as not doing so would result in significant left-truncation. I also drop all pairs with a value of 0 in both 1990 and 2000 for approach (b) (P4), as well as a small number of flows that failed to merge.

Labor demand shock construction

I construct wage and employment variants of the Bartik (1991) labor demand shock using Census microdata from 1990 and 2000. I exclude all workers in California. To create measures of national changes in labor demand, I calculate the change in wage or employment by two digit SIC industry from 1990 to 2000. I then interact this with the 1990 employment share by industry at each census tract of work to create a local measure of (plausibly exogenous) change in labor demand. While it would be preferable to use 1980 employment share by industry at tract of work, I have not been able to locate such data.

I then follow the approach described in Section 4 and interact the labor demand shock with the distance between tracts to model how the shock dissipates into adjacent markets. Because each tract may be joined to a different number of tracts, I weight by distance and exclude tracts that experience zero commuting flows (P3).

Data trimming

The various processes above produce relatively standardized data that accord reasonably well with ad hoc probes of quality. However, there are instances of extreme values that become influential observations during estimation. I experimented with a number of approaches to deal with this: (i) doing nothing, (iia) winsorizing in levels, (iib) trimming in levels, (iiia) winsorizing in changes, and (iiib) trimming in changes, where all winsorizing and trimming takes places at the 1st and 99th centiles. While I select (i) for all results reported in the main paper, the extended identification results for the labor demand elasticities use data cleaned according to (iiib), likely because it reduces the number of influential observations and removes observations with implausible-seeming characteristics from the data.

I also remove observations with top-coded data where applicable; this matters most for the estimation of ψ and recovery of residential amenities $\mathbf{B}$. If a variable was top-coded differently in different years, I standardize the top code to the most conservative year.

Travel time, route construction, and exposure to transit

Travel times were originally calculated using Dynamap data and ArcGIS, however, I no longer have access to that data. I also have calculated travel times using HERE's API `developer.here.com` to ensure that those numbers are reasonable (they are). In general, I use the Dynamap-generated travel times because it was based on an older model of the street network, and thus is more likely to match the driving environment under study (in 1990 and 2000) than HERE's travel times, which reflect the current street network.

To determine which driving routes were most exposed to LA Metro Rail, I use a local instance of Graphhopper, an open source routing engine. I provide it data from OpenStreetMap on all of Southern California, and feed it all combinations of pairs of origins and destinations. This returns a shapefile for each route. I intersect these routes with buffers of various distances around LA Metro Rail lines, and assign to each buffer bin the share of the route that lies within that bin.

Construction of treatment and control groups

The Dorothy Peyton Gray Transportation Library of LACMTA hosts historical data on proposed transit plans for the Los Angeles area, including the Kelker, De Leuw & Company (1925) plan. I obtain high-resolution digital copies of Plates 1 and 2 of this document and georeference them in ArcGIS using immutable landmarks and political boundaries.[F.3] I then trace the proposed lines and the existing PER lines from this map, and convert these traces into shapefiles.

To define treatment status, I spatially join shapefiles on actual LA Metro Rail stations from LACMTA to both census tract centroids and boundaries. I define treatment in two ways:

i) *O & D contain station*: Both tracts either contain a transit station or have their centroid within 500 meters of a transit station.

ii) *O & D <250m from station*: Some part of *both* tracts are within 250 meters of a transit station, but i) is not true.

iii) *O & D <500m from station*: Some part of *both* tracts are within 500 meters of a transit station, but neither i) nor ii) are true.

Only stations open before the end of 1999 are considered. Appendix Figure H5 uses a single measure treatment variable that determines treatment based on various combinations of maximum distances from centroid and perimeter to station. As expected, under very stringent definitions, the estimated effect is large and positive. As distances increase, the estimated effect drops to zero.

All treated tracts are included in all estimates. To develop a set of control tracts, I spatially join the shapefiles descended from the Kelker, De Leuw & Company (1925) document to the census tract shapefiles, and keep all tracts that have boundaries within 500 meters of the tracks. This assigns non-treated tracts to a control group for three different reasons: (i) They lie along spurs of proposed track that were never built, (ii) they are near a built track but distant from a station, or (iii) they lie slightly farther away from stations than nearby treated tracts. Previous iterations of this paper have used alternative definitions of these control groups, but the use of a 500 meter boundary seems to provide the closest comparison. I perform this separately for 1990 tract geographies (for the main specifications) and 2010 tract geographies (for use with the NCDB and LEHD LODES).

A.3 CTPP vs. LODES

I draw data primarily from the CTPP. There are a number of advantages and a few disadvantages of the CTPP over another popular source of data, the Longitudinal Employer-Household Dynamic (LEHD) Origin-Destination Employment Statistics (LODES). The benefits of CTPP data:

F.3. Maps available through the LACMTA library and online at https://www.metro.net/about/library/archives/visions-studies/mass-rapid-transit-concept-maps/.

1. In CTPP data, place of work is determined from household responses to a particular set of census questions. The response indicates where an individual worked in the week prior to the census, which may or may not correspond to a fixed establishment. LODES data come from federal tax records, and so identify people as working at the address on a firm's tax statement. Thus for firms with several establishments, there may be clustering at the mailing location that is not indicative of actual workplace. This is particularly true for large, multi-establishment firms.

2. The CTPP included median and mean wage at place of work prior in the 1990 and 2000 enumerations. LODES provides only a few large bins. Accurate measures of local wage at place of work are key to this analysis, and a novel contribution to the urban trade literature.

3. CTPP data include reported travel times. Thus, these estimates take into account congestion and other items unobservable to route planning GIS systems that may induce measurement error.

4. CTPP location data are accurately reported, while there is some geographic randomization (within block group) in LODES data to preserve confidentiality.

5. The CTPP data go back to 1990, while LODES does not begin until 2002. Thus, with CTPP I can fully capture commuting in 'pre' and 'post' periods.

Benefits of LODES data:

1. LODES data provide annual measures of commuting between locations since 2002, and the geocoding of workplace mailing address has a higher match rate than in the CTPP.

2. The CTPP has rather odd rounding rules that induce more measurement error in low commute-flow tract pairs. LODES has no such rounding rules (though there is geographic jittering).

3. LODES is calculated with consistent geography over time, while the CTPP is estimated using whatever geographies are decided upon by state census and transportation entities. This means that CTPP data must undergo geographic normalization, while LODES data do not.

There are two further disadvantages to the CTPP data: (i) Not all fields from the 1990 and 2000 CTPP are reported in the 2006/10 CTPP. Important for this paper is the lack of wage at place of work data in 2006/10. (ii) Industry coding changed between the 1990 and 2000 census reports.

I have tried combining data sources to provide a more complete panel of commuting flows across time. There are a number of issues with this approach, namely concern that measurement error in flows drowns out meaningful variation in observed commuting flow changes over time. In fact, this seems to be the case when combining the 1990 CTPP with 2002 LODES data, or the 1990 and 2000 CTPP data with more recent LODES data. Further, the lack of wage at place of work data in LODES is a severe disadvantage. While I have experimented with alternative (fixed effects) methods to estimate wage at place of work, measurement error swamps meaningful measurement.

A.4 Distance calculations on an idealized geography

To help interpret and contextualize the estimated coefficients on the commuting flow treatment bins in Section 4, I describe below functions of the distances implied by the treatment bins *on an idealized geography*. Real-world census tracts show a wide variety of shapes and vary in density in ways that make such calculations on actual geography challenging. The approach below abstracts away from from both random census tract shaping and variation in density within census tracts.

Suppose all locations on a map are covered by squares tracts with an identical area A; we will use the median tract area 1.38km^2 for the calculations below. This corresponds to a square with edges of length $\ell = \sqrt{A} = 1.17$km. Consider a station at the origin. We can calculate the average distance to a square with vertices (starting in the SW corner of the square and proceeding clockwise) at (a, b), $(a, b + \ell)$, $(a + \ell, b + \ell)$, $(a + \ell, b)$ by using the following expectation:

$$\int_b^{b+\ell} \int_a^{a+\ell} \frac{\sqrt{x^2 + y^2}}{A} dxdy$$

Note that this expectation is valid only under a uniform density in the square. It also uses straight-line distance: In the presence of buildings that obstruct straight-line walking paths, this measure will therefore understate the true distance. Denote by d_ϵ some tiny distance, positive distance to be used as a limit for the calculations below (i.e., it will equal 0m for calculation).

Table A1 maps the treatment bins presented in Section 4 to several descriptions of minimum, maximum, and average distance. The simple measure is *Range*, which is just the minimum and maximum distances from a station to a point in a tract that falls under definition i), ii), or iii). Under definition i), the minimum *Range* is just 0m and the range assumes a station located at a vertex of the tract. The minimum *Range* for definitions ii) and iii) are assuming the station is nearest to the midpoint of one side of the tract, at a perpendicular distance of d_ϵ and $250m$ respectively. The maximum *Range* assumes the station is located diagonally away from a vertex of the tract, with a perpendicular distance of $250m$ and $500m$

The *Station at centroid* measure assumes that a station is located at the centroid of the tract. The expectation above is therefore evaluated at the given values of a and b in the table; this corresponds to the average distance from the origin to any point in a square of area A that is centered at the origin. If the station is a centroid, however, no tracts can fall under definition ii) or iii), because the station is $\ell/2 > 500m$ from the nearest edge.

The *Minimum Average Distance* and *Maximum Average Distance* measures instead calculate the average distance from the station if were as close as possible or as far as possible, respectively, according to the expectation criteria above. For i), that means putting the station in the centroid of the tract or at a vertex of the tract. For ii), it means placing the station just outside the midpoint of an edge of the tract or 250m diagonally away from the vertex of the tract. For iii), it means placing the station 250m perpendicularly away from the midpoint of an edge of the tract or 500m diagonally away from the vertex of the tract. Numerical values of *Station at centroid*, *Minimum Average Distance*, and *Maximum Average Distance* were calculated using Wolfram Alpha's online integral evaluator (note that analytic solutions exist).

Table A1: Distances for different treatment bins under uniform square geography of median area

	Range	Station at centroid	Min. Ave. Dist.	Max. Ave. Dist.
Distances under i)	[0m, 1655m]	444m $a = -\frac{\ell}{2}$ $b = -\frac{\ell}{2}$	444m $a = -\frac{\ell}{2}$ $b = -\frac{\ell}{2}$	888m $a = -d_\epsilon$ $b = -d_\epsilon$
Distances under ii)	(0m, 2008m)	- $a = .$ $b = .$	689m $a = d_\epsilon$ $b = -\frac{\ell}{2}$	888m $a = d_\epsilon$ $b = d_\epsilon$
Distances under iii)	[250m, 2363m)	- $a = .$ $b = .$	901m $a = 250m + d_\epsilon$ $b = -\frac{\ell}{2}$	1219m $a = 250m + d_\epsilon$ $b = 250m + d_\epsilon$

B Proofs and Algebra

Proposition 1

To establish Proposition 1i (existence), I utilize a fixed point argument and homogeneity. To establish Proposition 1ii, I make use of Theorem 1ii from Allen, Arkolakis, and Li (2014) (AAL) and the Perron-Frobenius Theorem.

Existence in a closed economy: Land use is assumed to be predetermined. Denote the set of location pairs with positive land use for housing and production as $\mathcal{C} = \{ij : L_i^H > 0 \text{ and } L_j^Y > 0\}$, and the cardinality of $\mathcal{C}$ as $N_{\mathcal{C}}$. Assume that $L_i^H > 0 \Leftrightarrow \sum_s \pi_{is} > 0$ and $L_j^Y > 0 \Leftrightarrow \sum_r \pi_{rj} > 0$. The model can be entirely expressed in terms of the aggregate population $\bar{N}$, the data on land use, local fundamentals, travel costs, and commuting shares $\{L_i^H, L_j^Y, A_j, \tilde{B}_i, C_i, D_{ij}, E_j, T_i, \delta_{ij}, \pi_{ij}\}_{\forall ij \in \mathcal{C}}$. Note that the commuting shares and aggregate population are endogenous; all else is given.

The commuting share from ij can be written as an implicit function of the vector of all commuting shares, population, exogenous variables, and models parameters: Define $\mathcal{T}_{ij}(\boldsymbol{\pi}; \bar{N})$:

$$\mathcal{T}_{ij}(\boldsymbol{\pi}; \bar{N}) = \frac{\frac{\Lambda_{ij}}{\delta_{ij}^{\epsilon}} \cdot \frac{\breve{A}_j^{\epsilon}}{\left(\bar{N} \sum_r \pi_{rj}\right)^{\epsilon(1-\alpha)}} \cdot \left(\bar{N} \breve{C}_i \cdot \sum_s \frac{\pi_{is} \breve{A}_s}{\left(\bar{N} \sum_r \pi_{rs}\right)^{1-\alpha}}\right)^{\frac{-\epsilon\psi(1-\zeta)}{1+\psi}}}{\sum_r \sum_s \frac{\Lambda_{rs}}{\delta_{rs}^{\epsilon}} \cdot \frac{\breve{A}_s^{\epsilon}}{\left(\bar{N} \sum_{r'} \pi_{r's}\right)^{\epsilon(1-\alpha)}} \cdot \left(\bar{N} \breve{C}_r \cdot \sum_{s'} \frac{\pi_{rs'} \breve{A}_{s'}}{\left(\bar{N} \sum_{r'} \pi_{r's'}\right)^{1-\alpha}}\right)^{\frac{-\epsilon\psi(1-\zeta)}{1+\psi}}}$$

with $\breve{A}_j = \alpha A_j {L_j^Y}^{1-\alpha}$ and $\breve{C}_i = (1-\zeta) C_i^{1/\psi} {L_i^H}^{-1}$. An equilibrium of the model is the vector $\boldsymbol{\pi}$ and aggregate population $\bar{N}$ such that $\boldsymbol{\pi}$ is a fixed point of $\mathcal{T}_{ij}(\boldsymbol{\pi}; \bar{N})$ and the no spatial arbitrage condition is satisfied. First, note that $\mathcal{T}_{ij}(\boldsymbol{\pi}; \bar{N})$ is homogeneous of degree zero in $\bar{N}$, so $\mathcal{T}_{ij}(\boldsymbol{\pi}; \bar{N}) = \mathcal{T}_{ij}(\boldsymbol{\pi})$ and the existence of commuting shares is independent of aggregate population.

Consider $\mathcal{T}_{ij}(\boldsymbol{\pi})$. By assumption, for all $ij \in \mathcal{C}$, we have $L_i^H > 0$, $L_j^Y > 0$, and $\sum_r \pi_{rj} > 0$ and $\sum_s \pi_{is} > 0$. This implies that $\pi_{ij} \geq 0$, and $\pi_{ij} \leq 1$ because π represent shares. Stacking equations, equilibrium commuting shares are a fixed point $\mathcal{T}(\boldsymbol{\pi}^{FP}) = \boldsymbol{\pi}^{FP}$. The function $\mathcal{T} : [0,1]^{N_{\mathcal{C}}} \to [0,1]^{N_{\mathcal{C}}}$ is continuous and maps a compact, convex set into itself. Therefore, by the Brouwer fixed point theorem, an equilibrium vector $\boldsymbol{\pi}^{FP}$ exists. In a closed economy, aggregate population is fixed, so this establishes existence.

Existence in an open economy: In an open economy, existence of equilibrium follows from *Existence in a closed economy*, but also the no spatial arbitrage that requires expected utility to be equalized to $\bar{U}$ in equilibrium. Denote element ij of $\boldsymbol{\pi}^{FP}$ as π_{ij}. Rewriting the no spatial arbitrage condition:

$$\bar{N} = \left(\frac{\bar{U}}{\Gamma\left(\frac{\epsilon-1}{\epsilon}\right) \cdot \left(\sum_r \sum_s \frac{\Lambda_{rs}}{\delta_{rs}^{\epsilon}} \cdot \frac{\breve{A}_s^{\epsilon}}{\left(\bar{N} \sum_{r'} \pi_{r's}\right)^{\epsilon(1-\alpha)}} \cdot \left(\bar{N} \breve{C}_r \cdot \sum_{s'} \frac{\pi_{rs'} \breve{A}_{s'}}{\left(\bar{N} \sum_{r'} \pi_{r's'}\right)^{1-\alpha}}\right)^{\frac{-\epsilon\psi(1-\zeta)}{1+\psi}} \right)^{1/\epsilon}} \right)^{\frac{1}{1-\alpha\left(1+\frac{\psi(1-\zeta)}{1+\psi}\right)}}$$

Given $\boldsymbol{\pi}^{FP}$, existence requires that the preceding equation give a real, finite value of $\bar{N}$. This is the case so long as $\epsilon > 1$ and $\alpha \neq \frac{1+\psi}{1+\psi(2-\zeta)}$.

Uniqueness: Consider now the set of places with the either positive land use for housing or for production, denoted $\mathcal{J}$ (a theorem referenced below requires that the set of possible housing locations be the same as the set of possible production locations). Rearranging the system in Equations (4), (6), (8), (9), and (10) into a more convenient form gives:

$$\begin{aligned} W_j^{\frac{1+\epsilon(1-\alpha)}{1-\alpha}} \Psi_j &= \bar{N}^{-1} K_{0j} \sum_{s\in\mathcal{J}} W_s^{\epsilon} \Psi_s \\ \Psi_j &= \sum_{r\in\mathcal{J}} K_{1rj} Q_r^{-\epsilon(1-\zeta)} \\ Q_i^{-\epsilon(1-\zeta)-\frac{1+\psi}{\psi}} \Phi_i &= \bar{N}^{-1} K_{2i} \sum_{s\in\mathcal{J}} W_s^{\epsilon} \Psi_s \\ \Phi_i &= \sum_{r\in\mathcal{J}} K_{1is} W_s^{\epsilon+1} \end{aligned}$$

where $K_{0j} = \breve{A}_j^{1/(1-\alpha)}$, $K_{1ij} = \Lambda_{ij}\delta_{ij}^{-\epsilon}$, and $K_{2i} = \breve{C}_i^{-1/\psi^2}$ are functions of predetermined parameters.

This transforms the model into the form of Equation 1 in AAL. Let $\mathbb{G}$ represent the matrix of exponents on the left hand side of the above system in the order (W, Ψ, Q, Φ), and let $\mathbb{B}$ be the corresponding exponents on the right hand side:

$$\mathbb{G} = \begin{pmatrix} \frac{1+\epsilon(1-\alpha)}{1-\alpha} & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -\epsilon(1-\zeta) - \frac{1+\psi}{\psi} & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \quad \mathbb{B} = \begin{pmatrix} \epsilon & 1 & 0 & 0 \\ 0 & 0 & -\epsilon(1-\zeta) & 0 \\ \epsilon & 1 & 0 & 0 \\ \epsilon+1 & 0 & 0 & 0 \end{pmatrix}$$

Note that $\mathbb{G}$ is invertible. To address uniqueness, define $\mathbb{A} = \mathbb{B}\mathbb{G}^{-1}$ and $\mathbb{A}^{+}$ to be the element-wise absolute value of $\mathbb{A}$. That is,

$$\mathbb{A}^{+} = \begin{pmatrix} \frac{\epsilon[(1-\alpha)-\mu]}{1+\epsilon(1-\alpha)} & \frac{1}{1+\epsilon(1-\alpha)} & 0 & 0 \\ 0 & 0 & \frac{\epsilon(1-\zeta)}{\epsilon(1-\zeta)+\frac{1+\psi}{\psi}} & \frac{\epsilon(1-\zeta)}{\epsilon(1-\zeta)+\frac{1+\psi}{\psi}} \\ \frac{\epsilon[(1-\alpha)-\mu]}{1+\epsilon(1-\alpha)} & \frac{1}{1+\epsilon(1-\alpha)} & 0 & 0 \\ \frac{(\epsilon+1)[(1-\alpha)-\mu]}{1+\epsilon(1-\alpha)} & \frac{(\epsilon+1)(1-\alpha)}{1+\epsilon(1-\alpha)} & 0 & 0 \end{pmatrix}$$

Theorem 1ii in AAL establishes that there is a unique equilibrium to the model if the spectral radius (largest eigenvalue) of $\mathbb{A}^{+}$ is less than or equal to one. Thus, uniqueness is established when $\rho(\mathbb{A}^{+}) \leq 1$.

Because $\mathbb{A}^{+}$ corresponds to a strongly connected graph and is nonnegative, it is irreducible. The Perron-Frobenius Theorem states that a nonnegative, irreducible matrix has a positive spectral radius with corresponding strictly positive eigenvector. So finding a condition under which $\rho(\mathbb{A}^{+}) \leq 1$ is identical to determining conditions under which $\mathbb{A}^{+}\mathbf{x} \leq \mathbf{x}$ for $\mathbf{x} \gg 0$. Solving the implied system of inequalities gives condition (11).[B.1]

Proposition 2

Existence: A_i is uniquely determined from:

$$A_i = \frac{W_i}{\alpha}\left(\frac{\sum_r \bar{N}\pi_{ri}}{L_i^Y}\right)^{1-\alpha}$$

and C_i is uniquely determined from:

$$C_i = Q_i^{1+\psi}\left(\frac{L_i^H}{\sum_s \bar{N}\pi_{is}W_s}\right)^{\psi}$$

Define an excess demand function:

$$\mathcal{D}_{ij}(\mathbf{\Lambda}) = \pi_{ij} - \frac{\Lambda_{ij}W_j^{\epsilon}\left(\delta_{ij}Q_i^{1-\zeta}\right)^{-\epsilon}}{\sum_r\sum_s \Lambda_{rs}W_s^{\epsilon}\left(\delta_{rs}Q_r^{1-\zeta}\right)^{-\epsilon}} = 0$$

Note that $\mathcal{D}$ is continuous and homogeneous of degree zero. Homogeneity implies that $\mathbf{\Lambda}$ can be rescaled and restricted to the unit simplex: $\{\mathbf{\Lambda} : \sum_r\sum_s \Lambda_{rs} = 1\}$. This means that $\mathcal{D} : [0,1]^{N^2} \to [0,1]^{N^2}$. So $\mathcal{D}$ is a continuous function from a compact, convex set into itself; the Brouwer fixed point theorem guarantees existence.

Uniqueness: To establish uniqueness, note that by homogeneity of degree zero, we have $\sum_r\sum_s \mathcal{D}_{rs}(\mathbf{\Lambda}) = 0$. Define $M_{ij} = W_j^{\epsilon}\left(\delta_{ij}Q_i^{1-\zeta}\right)^{-\epsilon}$. The Jacobian of $\mathcal{D}$ has diagonal elements:

$$-\frac{M_{ij}\cdot\left(\left(\sum_r\sum_s \Lambda_{rs}M_{rs}\right) - \Lambda_{ij}M_{ij}\right)}{\left(\sum_r\sum_s \Lambda_{rs}M_{rs}\right)^2} < 0$$

and off-diagonal elements

$$\frac{\Lambda_{ij}M_{ij}M_{\{ij\}'}}{\left(\sum_r\sum_s \Lambda_{rs}M_{rs}\right)^2} > 0$$

where $\{ij\}'$ refers to an origin destination pair such that $i' \neq i$ and/or $j' \neq j$. Thus the aggregate excess demand function exhibits gross substitution, and equilibrium is unique.[B.2]

B.1. To ensure the algebra is correct, I have numerically verified $\rho(\mathbb{A}^{+}) \leq 1$ iff Equation (11) holds.

B.2. See Proposition 17.F.3 in Mas-Colell, Whinston, and Green, *Microeconomic Theory* (Oxford University Press, 1995). An alternative approach could be to use weak diagonal dominance of this positive matrix (following Bayer and Timmins (2005) but for weaker conditions).

Rewriting the Model as a Three Linear Equation System

Taking logs of Equations (4), (6), and (8) gives the following cross-sectional system (where lower-case letters represent the log counterparts of level variables):

$$w_j = g_0 + (\alpha - 1)n_j^Y + \ln(A_j) \tag{1}$$
$$n_{ij} = g_1 + \epsilon w_j - \epsilon(1-\zeta)q_i - \epsilon\kappa\tau_{ij} + \ln(B_i E_j D_{ij}) \tag{2}$$
$$q_i = g_2 + \psi h_i + \ln(C_i) \tag{3}$$

where $n_j^Y = \ln\left(\bar{N}\sum_r \pi_{rj}/L_j^Y\right)$ is log employment density and $h_i = \ln\left((1-\zeta)\bar{N}\sum_s \pi_{is}W_s/Q_i L_i^H\right)$ is log housing density. The g capture remaining constants: $g_0 = \ln(\alpha)$, $g_1 = \ln(\bar{N}) - \ln\left(\sum_r\sum_s \Lambda_{rs}\left(e^{\kappa\tau_{rs}}Q_r^{1-\zeta}\right)^{-\epsilon} W_s^{\epsilon}\right)$, and $g_2 = 0$. Local fundamentals are potentially functions of covariates ($A = A(X)$ and so on) such as transit proximity.

This system can be re-expressed to more clearly represent the supply and demand linkages and better exposit the identification strategy. First, separate the unobservables into time-varying and time-invariant components, so that $\ln(A_{jt}) = \bar{a}_j + a_{jt}$, etc. Under the assumption that land use and travel times are constant, this means making the structural assumptions:

$$\ln(A_{jt}L_{jt}^{Y\,1-\alpha}) = \bar{a}_j + a_{jt} \tag{4}$$
$$\ln(B_{it}E_{jt}D_{ijt}) = \bar{b}_i + b_{it} + \bar{e}_j + e_{jt} + \bar{d}_{ij} + d_{ijt} \tag{5}$$
$$\ln(C_{it}L_{it}^{H\,-\psi}) = \bar{c}_i + c_{it} \tag{6}$$

Relaxing this to allow for exogenous changes in land use is straightforward. Doing so, and preserving the notation above leads to the following system:

$$\text{Labor demand in } j: \quad w_{jt} = g_{0t} + \tilde{\alpha}n_{jt}^Y + \bar{a}_j + a_{jt} \tag{7}$$
$$\text{Labor supply to } j: \quad \omega_{jt} = \epsilon w_{jt} + \bar{e}_j + e_{jt} \tag{8}$$
$$\text{Commuting between } i \text{ and } j: \quad n_{ijt} = g_{1t} + \omega_{jt} + \theta_{it} - \epsilon\kappa\tau_{ijt} + \bar{d}_{ij} + d_{ijt} \tag{9}$$
$$\text{Housing demand in } i \quad \theta_{it} = \tilde{\zeta}q_{it} + \bar{b}_i + b_{it} \tag{10}$$
$$\text{Housing supply in } i: \quad q_{it} = g_{2t} + \psi h_{it} + \bar{c}_i + c_{et} \tag{11}$$

where $\tilde{\alpha} = \alpha - 1$, $\tilde{\zeta} = -\epsilon(1-\zeta)$. The system resembles standard linear supply and demand models, but for many interconnected housing and labor markets.

Welfare under $\epsilon \leq 1$ (Frechet is Multinomial Logit)

First, I show that the expression in Equation (16) has an equivalent log-sum representation. Begin by dividing counterfactual and factual expected utilities (from Equation 5):

$$\hat{\hat{U}} = \frac{\mathbb{E}[U'_{ijo}]}{\mathbb{E}[U_{rso}]} = \frac{\Gamma\left(\frac{\epsilon-1}{\epsilon}\right)\cdot\left(\sum_{\{ij\}}\tilde{\Lambda}'_{ij}\left(\delta'_{ij}Q_i'^{1-\zeta}\right)^{-\epsilon}(\tilde{B}'_iW'_j)^{\epsilon}\right)^{1/\epsilon}}{\Gamma\left(\frac{\epsilon-1}{\epsilon}\right)\cdot\left(\sum_{\{rs\}}\tilde{\Lambda}_{rs}\left(\delta_{rs}Q_r^{1-\zeta}\right)^{-\epsilon}(\tilde{B}_rW_s)^{\epsilon}\right)^{1/\epsilon}} = \left(\frac{\sum_{\{ij\}}\tilde{\Lambda}'_{ij}\left(\delta'_{ij}Q_i'^{1-\zeta}\right)^{-\epsilon}(\tilde{B}'_iW'_j)^{\epsilon}}{\sum_{\{rs\}}\tilde{\Lambda}_{rs}\left(\delta_{rs}Q_r^{1-\zeta}\right)^{-\epsilon}(\tilde{B}_rW_s)^{\epsilon}}\right)^{1/\epsilon} \tag{12}$$

where $\{ij\} = \{rs\}$ track summation sets. Substituting in Equation (4) for some particular ij into the above twice (once for π'_{ij} and once for π_{ij}) and taking logs gives Equation (16).

From Train (2009), the change in consumer welfare due to changes of the characteristics of the elements in the choice set is:

$$\mathbb{E}[\bar{\mathcal{W}}'] - \mathbb{E}[\bar{\mathcal{W}}] = \frac{1}{\mu}\ln\left(\frac{\sum_{k\in K_1}e^{V'_k}}{\sum_{k\in K_0}e^{V_k}}\right) \tag{13}$$

where here μ is the marginal utility of income.[B.3] Let:

$$\begin{aligned} V'_k &= \ln\left(\tilde{\Lambda}'_{ij}\left(\delta'_{ij}Q_i'^{1-\zeta}\right)^{-\epsilon}(\tilde{B}'_iW'_j)^{\epsilon}\right) \\ V_k &= \ln\left(\tilde{\Lambda}_{rs}\left(\delta_{rs}Q_r{}^{1-\zeta}\right)^{-\epsilon}(\tilde{B}_rW_s)^{\epsilon}\right) \\ \mu &= \epsilon \\ K_0 = K_1 &= \{ij\} = \{rs\} \end{aligned}$$

Taking logs of Equation F-1 then delivers Equation F-2. Note that $\mu = \epsilon$ is natural as ϵ already captures the utility effect of wage dollars. Thus the Frechet framework is identical to a multinomial logit framework where the utility from choice ij is:

$$\mathcal{U}_{ijo} = \ln\left(\tilde{\Lambda}'_{ij}\left(\delta'_{ij}Q_i'^{1-\zeta}\right)^{-\epsilon}(\tilde{B}'_iW'_j)^{\epsilon}\right) + \varepsilon_{ijo}$$

for ϵ_{ijo} distributed iid extreme value. In fact, this is very precisely (up to interpretation of amenity terms and trade costs) the specification often used in the discrete location choice literature (e.g., Bayer, Keohane, and Timmins 2009). To map interpretation of the change in consumer welfare between the two frameworks, note:

$$\mathbb{E}[\bar{\mathcal{W}}'] - \mathbb{E}[\bar{\mathcal{W}}] = \ln\mathbb{E}[U'_{ijo}] - \ln\mathbb{E}[U_{ijo}] = \ln\hat{\hat{U}} \approx \%\Delta\ \text{Welfare}$$

B.3. Thanks to Wei You for noting that (16) and a log-sum expression are interchangeable:

$$\hat{U} = \left(\frac{\hat{\hat{\Lambda}}_{ij}(\hat{\tilde{B}}_i\hat{W}_j)^{\epsilon}\hat{Q}_i^{-\epsilon(1-\zeta)}}{\hat{\pi}_{ij}}\right)^{1/\epsilon} = \left(\sum_{\{ij\}}\pi_{ij}\hat{\tilde{\Lambda}}_{ij}\left(\hat{\delta}_{ij}\hat{Q}_i^{1-\zeta}\right)^{-\epsilon}(\hat{\tilde{B}}_i\hat{W}_j)^{\epsilon}\right)^{1/\epsilon}$$

That is, welfare change is naturally expressed in relative terms (rather than monetary terms) when used with Frechet framework. Equation F-2 only requires $\epsilon > 0$, and so Equation (16) can be used for welfare evaluation when $\epsilon \in (0, 1]$ and well as $\epsilon > 1$.

C Cost-benefit Calculations

This section details the costs of the subway built by 2000. I do not track costs since 2000, as the calculation becomes much less clear with more recent data. To compare the costs and benefits of transportation interventions, I require annualized estimates of costs to compare with the annualized welfare benefits calculated in the text. Costs consist of two components: (i) the annualized cost of capital investment in rail, rail cars, stations, and similar expenses, and (ii) net operating expenses (operating costs less revenues).

$$\text{Total Annual Cost} = \text{Operating Subsidy} + \text{Annualized Capital Expenditure}$$

C.1 Annualized Capital Expenditure

Cost information is from a consolidation of capital expenditures on lines built before 2000 from fiscal budgets.[C.1] After adjusting all costs to 2015 dollars, the total capital expenditure for the rail, rolling stock, and stations built prior to 2000 is \$8.7 billion. To annualized this, I assume annual payments are made on this principal balance over a 30-year horizon with 6% interest rate (the interest rate used for some internal calculations by LA Metro). This gives an annualized capital cost of \$634.6 million. This does not include other financing charges, the cost of planning, or some other expenses.

However, LA Metro's internal cost of borrowing may not be a suitable social discount rate, and the 30-year horizon may be too short. I provide several alternative definitions: (i) 5% interest over a 50-year horizon, (ii) 5% over an infinite horizon, and (iii) 2.5% over an infinite horizon. For (i) and (ii), the 5% rate is roughly equal to a low-yielding municipal bonds in 2000. For (iii), the 2.5% rate is low, roughly equal to the recent cost of borrowing, and is meant to represent a policy maker that highly values future generation or is uncertain about future discount rates (see Weitzman 1998). Once built, subways typically remain in operation for the long run (perhaps forever).

C.2 Operating Subsidies

Like most transit systems in the United States, LA Metro has incomplete farebox recovery, meaning that it subsidizes a portion of every ride. For rail in 2001, the farebox recovery ratio was about 20%. To estimate the welfare effects, I use the *net* subsidy: operating costs less fare revenue. Operating expenses from 1999 or 2000 are unavailable, so I use operating expenses from 2001 and 2002 as a proxy. Rail (light and heavy) operations total \$202.4 million in 2015 dollars, and rail fare revenue is \$40.2 million. The net subsidy is \$162.2 million per year.

C.1. Source: `http://demographia.com/db-rubin-la-transit.pdf`.

D Model Extensions and Alternative Identification

D.1 Additional Identification Methods and Results

This section extends the approach of interacting labor demand shocks with geography to identify the remaining (housing and labor demand) elasticities. I also discuss two modifications to the standard identification framework: (i) endogenous land use determination (no zoning), and (ii) the presence of agglomeration and other forces.

Residents of one location commute to many different locations for work. Workers who live in i and work in j are sensitive to the housing demands of workers who work in j' but also live in i. A labor demand shock to workers ij' can change the effective housing supply to workers ij. Thus labor demand shocks for ij' workers can be used to instrument changes in housing prices for ij workers and identify the slope of housing demand. To develop an average measure of the shocks for $ij', j' \neq j$, I employ inverse weighting as before, but exclude own tract j:

$$\Delta z^{HS}_{i(-j)t}(\rho) = \sum_{s \neq j} \frac{e^{-\rho\delta_{is}} 1_{\check{n}_{is}>0} \Delta z_{st}}{\sum_{s \neq j} e^{-\rho\delta_{is}} 1_{\check{n}_{is}>0}}$$

Note that place of work-by-year fixed effects (ω_{jt}) control for changes in workplace amenities. The following moment condition identifies $\tilde{\zeta} = \epsilon(1-\zeta)$:

$$\mathbb{E}[\Delta z^{HS}_{i(-j)t}(\rho) \times (\Delta b_{it} + \Delta d_{ijt})] = 0, \ \forall\, i, j' \neq j \tag{M-3}$$

This instrument varies for every commuting pair. It is generally difficult to recover estimates of housing demand without microdata due to difficulties in quantifying housing services. Nonetheless, because tract pairs express more variation than individual tracts, this approach can identify the housing demand elasticity.

Finally, workers employed at j observe the labor demand shock to $j' \neq j$, and may respond by leaving j for j'. This suggests that a labor demand shock at j' can be used to instrument changes in employment at j, functioning as a labor supply shock in j and identifying labor demand. But this is reflected through residential location, rather than through location at place of work. Consider residents in i: A positive shock to j' entices more workers from i the closer j' is to i, rather than the closer j' is to j. The following weighting uses this intuition and interacts with distance twice:

$$\Delta z^{LS}_{jt}(\rho) = \sum_r \left(\frac{e^{-\rho\delta_{rj}} 1_{\check{n}_{rj}>0}}{\sum_r e^{-\rho\delta_{rj}} 1_{\check{n}_{rj}>0}} \sum_{s \neq j} \frac{e^{-\rho\delta_{sr}} 1_{\check{n}_{is}>0} \Delta z_{st}}{\sum_{s \neq j} e^{-\rho\delta_{sr}} 1_{\check{n}_{is}>0}} \right)$$

The own tract labor demand shock is excluded in order to remove mechanical correlation with local changes in productivity. The corresponding moment condition is:

$$\mathbb{E}[\Delta z^{LS}_{jt}(\rho) \times \Delta a_{jt})] = 0, \ \forall j \tag{M-4}$$

This identifies the labor demand elasticity, $\tilde{\alpha} = \alpha - 1$, and provides an alternative way to estimate this parameter that is conceptually similar to the competing characteristics instrument of Berry, Levinsohn, and Pakes (1995).

Because the instruments described above are all weighted averages of the labor demand shock, the identifying assumptions can be made more transparent. The following reframe M-1 through M-4 in terms of a labor demand shock (note A-1 is identical to M-1):

$$\mathbb{E}[\Delta z_{jt} \times (\Delta e_{jt} + \Delta d_{ijt})] = 0,\ \forall\, ij \tag{A-1}$$

$$\mathbb{E}[\Delta z_{jt} \times \Delta c_{it}] = 0,\ \forall\, ij \tag{A-2}$$

$$\mathbb{E}[\Delta z_{j't} \times (\Delta b_{it} + \Delta d_{ijt})] = 0,\ \forall\, ij' \neq ij \tag{A-3}$$

$$\mathbb{E}[\Delta z_{j't} \times \Delta a_{jt}] = 0,\ \forall\, j' \neq j \tag{A-4}$$

Proposition 3. *Assume A1, A2, A3, and A4 are true, $\rho > 0$, $\mathbb{E}[\Delta z_{jt} \times \Delta w_{jt}] \neq 0$, housing demand is downward sloping, and labor and housing supply are upward sloping. Then M1, M2, M3, and M4 are satisfied and the model is identified.*

Proof. Assumptions A-1 to A-4 are derived from M-1 to M-4 using the definitions of the instruments. The requirement that $\rho > 0$ ensures variation in the labor demand shock across space. The requirements are standard regularity conditions for identification in a system of simultaneous equations. □

Furthermore, data on commuting flows and workplaces wages in combination with Equation (13) suggest high-dimensional fixed effects can help control for unobserved confounders. Assumptions A-1 and A-3 can be weakened to exploit this:

$$\mathbb{E}[\Delta z_{jt} \times \Delta e_{jt}] = 0,\ \forall\, j \tag{A-1a}$$

$$\mathbb{E}[\Delta z_{jt} \times \Delta c_{it}] = 0,\ \forall\, i \neq j \tag{A-2a}$$

$$\mathbb{E}[\Delta z_{j't} \times \Delta b_{it}] = 0,\ \forall\, i \tag{A-3a}$$

It is difficult to estimate household expenditure shares or labor demand elasticities in urban models that use aggregated data (e.g., Diamond 2016). Table D1 uses the employment variant of $\Delta z^{HS}_{i(-j)t}$ to instrument for housing prices to determine $\epsilon(1-\zeta)$, the elasticity of housing demand. The own tract can be excluded from the regression to limit concerns about the labor demand shock driving confounding changes in amenities. Results are significant and vary between -1.00 and -0.78. With $\epsilon = 2.18$, these imply a housing expenditure share between 36% and 45% of income, somewhat higher than microdata suggest but not unreasonable for high cost areas.

Table D1: IV estimates of housing demand elasticity ($-\epsilon(1-\zeta)$)

	$\Delta n_{ijt} = \Delta \ln(N_{ijt})$		
	(1)	(2)	(3)
A. IV Estimates of $-\epsilon(1-\zeta)$			
$\Delta \ln(\text{House Value})$	-0.782**	-0.778**	-1.008***
	(0.378)	(0.377)	(0.382)
B. First Stage			
$\Delta z^{HS}_{i(-j)t}(\rho)$	1.139***	1.140***	1.135***
	(0.074)	(0.074)	(0.074)
F-stat (CD)	363.2	364.0	356.5
F-stat (KP)	239.7	240.0	236.5
N	143593	143593	141188
Sample	All	All	not ii
Travel Time	-	Y	-

Panel instrument variable (IV) estimates of regression of flows on median housing values, using $\ln(\rho) = -5.5$. Estimated in differences using employment instrument. CD and KP refer to the Cragg-Donald and Kleibergen-Paap tests, respectively. Variables are trimmed to exclude extreme values (see text). All estimates include tract-of-work-by-year and tract-pair fixed effects. Standard errors clustered by tract in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, I estimate the inverse elasticity of labor demand ($\alpha - 1$) using demand shocks to nearby census tracts as an instrument. Results, shown in Table D2 vary substantially. Column 2 of Table D2 includes the own-tract demand shock, Δz_{jt}, as a control (recall that the instrument is $\Delta z^{LS}_{jt}(\rho)$). This permits limited spatial correlation (to the extent the observed labor demand shocks are spatially correlated), and implies a slightly higher labor share of income. The measure may not be unreasonable, particularly given the power of the first stage results (the magnitude is less interpretable because of repeated aggregation across origins and destinations). Column C includes the log measure of land zoned for productive uses, but this is measured poorly in the data.[D.1] Similarly, Column D indicates too large estimates.

D.1. Unlike residential land, it is difficult to classify different types of land used in production. For example, it is unclear whether to add land used for storage. Further, the data show some unusual changes across waves.

Table D2: IV estimates of inverse labor demand elasticity $(\alpha - 1)$

	$\Delta w_{jt} = \Delta \ln(W_{jt})$			
	(1)	(2)	(3)	(4)
A. IV Estimates of $(\alpha - 1)$				
$\Delta \ln(\text{Employment})$	-0.679*	-0.346*	-1.389	
	(0.382)	(0.179)	(1.595)	
$\Delta \ln(\text{Prod. Land})$			1.806	
			(2.050)	
$\Delta \ln(\text{Emp. Density})$				-0.999
				(0.888)
B. Specification Test $(H_0 : \psi_{\text{Employment}}/\psi_{\text{Prod. Land}} = -1)$				
$\psi_{\text{Employment}}/\psi_{\text{Prod. Land}}$			-0.769	
$[\cdot] = \Pr(H_0)$			[0.004]	
C. First Stage				
$\Delta z_{jt}^{LS}(\rho)$	-15.205**	-22.181***	-6.625	-8.878
	(7.367)	(7.747)	(7.242)	(7.245)
F-stat (CD)	5.4	10.6	1.0	1.9
F-stat (KP)	4.3	8.2	0.8	1.5
N	2442	2442	2385	2385
Own shock as control	-	Y	Y	Y

Panel instrument variable (IV) estimates of regression of employment, employment density and land in production, using $\ln(\rho) = -5.5$. CD and KP refer to the Cragg-Donald and Kleibergen-Paap tests, respectively. Variables are trimmed to exclude extreme values (see text). Columns 2-4 include the own tract labor demand shock as a control. Standard errors clustered by tract in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Reasonable estimates of $\tilde{\alpha}$ and $\tilde{\zeta}$ provide confidence in this interconnected approach to identification and serve as an informal test of overidentification. Estimation of these parameters is more demanding than ϵ and ψ, both in terms of the stringency of the moment conditions and in the amount of exogenous variation needed to avoid weak instrument problems. Overall, these results suggest that interacting locally defined labor demand shocks with spatial structure can be used to create broad, omnipurpose tools for identifying local price elasticities.

D.2 Extension with externalities

I also consider a model extension with production and residential externalities. I model these as in Ahlfeldt et al. (2015), who define production and residential externalities as an inverse-distance weighted sum of employment and residential population, respectively. This recasts endogenous measures of productivity and amenities in terms of an exogenous fundamental, the observable distribution of population, and four new parameters. Specifically,

$$A_j = \mathcal{A}_j \Upsilon_j^{\mu}, \qquad \Upsilon_j = \sum_n \frac{e^{\kappa_A d_{jn}} \sum_r \pi_{rn}}{L_j^Y}$$
$$B_i = \mathcal{B}_i \Omega_i^{\eta}, \qquad \Omega_i = \sum_n \frac{e^{\kappa_B d_{ni}} \sum_s \pi_{ns}}{L_i^H}$$

where I use parameters from Ahlfeldt et al. (2015) as needed.

If the parameters for the spillovers are known (of both the effects and the distance functions), then it is not necessary to develop new identification assumptions. Instead, the following substitutions can be made:

$$w_{jt} - \mu \ln(\Upsilon_{jt}) \text{ for } w_{jt} \text{ in the labor demand equation}$$
$$\theta_{it} - \eta \ln(\Omega_{it}) \text{ for } \theta_{it} \text{ in the housing demand equation}$$

Note that these equations reveal why the presence of these forces has little effect in this setting: They are mostly captured by the fixed effects $\bar{a}_j$ and $\bar{b}_i$.

If the spillovers are omitted from the model, additional moment conditions are required. Moment conditions presented in Assumptions A-1, A-1a, A-2, and A-2a do not change. Recall that those assumptions identify the key parameters of interest. Moment conditions corresponding to A-3, A-3a, and A-4 are tightened:

$$\mathbb{E}[\Delta z_{j't}^{LD,R} \times \Delta \ln(B_{it}\Omega_{it}D_{ijt})] = 0, \; \forall\, ij' \neq ij$$
$$\mathbb{E}[\Delta z_{j't}^{LD,R} \times \Delta \ln(B_{it}\Omega_{it})] = 0, \; \forall\, i$$
$$\mathbb{E}[\Delta z_{j't}^{LD,R} \times \Delta \ln(A_{jt}\Upsilon_{jt})] = 0, \; \forall\, j' \neq j$$

For these to hold, two additional assumptions are required in addition to Assumptions A-3 (or A-3a) and A-4:

$$\mathbb{E}[\Delta z_{j't}^{LD,R} \times \Delta \ln(\Omega_{it})] = 0, \; \forall\, i \tag{S-3}$$
$$\mathbb{E}[\Delta z_{j't}^{LD,R} \times \Delta \ln(\Upsilon_{jt})] = 0, \; \forall\, j' \neq j \tag{S-4}$$

If these conditions hold in addition to Assumptions A, the model is identified.

However, recall that instrument relevant requires $\mathbb{E}[\Delta z_{jt}^{LD,R} \times \Delta \ln(A_{jt})] \neq 0$. Both Ω and Υ depend on nearby density, so to the extent location j' is near i or j, productivity shocks influence density and Assumptions S-3 and S-4 are unlikely to hold in a strict sense. However, they may hold approximately: There is significant autocorrelation in the population mass in locations from decade to decade. While this makes separately identifying agglomeration force difficult, in the context of the model presented here, this stickiness aids identification because much of $\Delta\Omega$ and $\Delta\Upsilon$ are captured by time-invariant tract fixed effects.

D.3 Endogenous Land Use

If land use is observed (as here) and the amount of land used in housing and production is determined by market forces, no additional assumptions need be made for identification. This is not true for the theoretical model or counterfactual simulations; both would need to be modified with an additional market clearing condition to account for the additional degree of freedom.

One minor change in interpretation of parameter values must be made if land use is endogenous. The assumption of congestion in the relationship between land price and residential density can no longer be supported: $P_i^L \neq (H_i/L_i^H)^{\tilde{\psi}}$. This is because of the price of land also depends on the demand for land for production (and so congestion occurs through displacing employment instead of density costs). ψ has no role in this alternate model. However, because total output (housing) is observable, we can modify the model to derive an estimating equation very similar to that in the main paper.

Consider the developer's problem. Zero profits implies $Q_i H_i = P_i^L L^H + P^M M$, and the first order conditions deliver an expression for M under profit maximization. This results in the expression:

$$Q_i H_i = \frac{1}{\phi} P_i^L L^H$$

which just requires that a constant fraction of developer income be spent on land. Solving this for P_i^L and substituting into Equation (6) and solving for Q_i delivers the equilibrium expression:

$$Q_i = \left(\frac{H_i}{L_i^H}\right)^{\frac{\phi}{1-\phi}} \mathfrak{C}_i$$

where $\mathfrak{C}_i = \frac{1-\phi}{\phi^2} P_M \tilde{C}_i^{1/(\phi-1)}$ contains the same elements as C_i. In fact, the estimating equation based on the above expression is isomorphic to that in the main text. Here, however, we identify $\frac{\phi}{1-\phi}$ instead of ψ. Note that under this interpretation, ϕ (the share of land in construction costs) is between 0.54 and 0.66. This is higher than a relatively standard value of 0.25 from Combes, Duranton, and Gobillon (2012), Epple, Gordon, and Sieg (2010), and Ahlfeldt et al. (2015). However, in Southern California land value anecdotally makes up high share of transacted real estate value. Alternatively, this could be seen as evidence in favor in immutable zoning.

As a quick aside, to complete the theoretical model, it is necessary to specify a land market clearing condition. I assume that the total land in a tract available for any use is fixed at $\bar{L}_i$; market clearing then requires $L_i^H + L_i^Y = \bar{L}_i$.[D.2] This condition can be rewritten (using Equation 4):

$$H_i \left(\frac{\mathfrak{C}_i}{Q_i}\right)^{\frac{1-\phi}{\phi}} + N_i^Y \left(\frac{W_i}{\alpha A_i}\right)^{\frac{1}{1-\alpha}} = \bar{L}_i$$

This equation, in conjunction with the model in the main text, is sufficient to pin down land use.[D.3]

D.2. Note that this implies $\Delta L_{it}^Y = -\Delta L_{it}^H$.

D.3. Note that we can also rewrite this market clearing condition as an analytic expression of the observable prices, quantities, parameters, and the unobservable price of land:

$$\frac{\phi Q_i H_i}{P_i^L} + N_i^Y \left(\frac{(1-\alpha) W_i N_i^Y}{\alpha P_i^L}\right)^{\frac{1}{\alpha}} = \bar{L}_i$$

The price and land can be be calculated from this expression.

D.4 Agglomeration and Endogenous Land Use

Because endogenous land use did not alter identification, identification with both agglomeration and endogenous land use requires the same assumptions as for the case with agglomeration: Assumptions S-3 and S-4 in addition to Assumptions A.

E Counterfactual Estimation & Bootstrap Procedure

E.1 Counterfactual Estimation

First, note that the following hold:

$$\hat{W}_i = \hat{A}_i \hat{\hat{N}}^{\alpha-1} \left(\frac{\sum_r \pi_{ri} \hat{\pi}_{ri}}{\sum_r \pi_{ri}} \right)^{\alpha-1} \tag{E1}$$

$$\hat{Q}_i = \hat{C}_i^{1/(1+\psi)} \left(\frac{\hat{\hat{N}} \sum_s \pi_{is} \hat{\pi}_{is} W_s \hat{W}_s}{\sum_s \pi_{is} W_s} \right)^{\psi/(1+\psi)} \tag{E2}$$

$$\hat{\pi}_{ij} = \frac{\hat{B}_i \hat{E}_j \hat{D}_{ij} \hat{W}_j^{\epsilon} \hat{Q}_i^{-\epsilon(1-\zeta)}}{\sum_r \sum_s \pi_{rs} \hat{B}_r \hat{E}_s \hat{D}_{rs} \hat{W}_s^{\epsilon} \hat{Q}_r^{-\epsilon(1-\zeta)}} \tag{E3}$$

where $\hat{\hat{N}} = 1$ in a closed economy. In the case of the open economy, aggregate population can adjust, ensuring no arbitrage between the city and outside locations. To account for this, define:

$$\hat{\hat{N}} = \left(\sum_r \sum_s \pi_{rs} \hat{B}_r \hat{D}_{rs} \left(\hat{A}_s \left(\frac{\sum_{r'} \pi_{r's} \hat{\pi}_{r's}}{\sum_{r'} \pi_{r's}} \right)^{\alpha-1} \right)^{\epsilon} \times \left(\hat{C}_r \cdot \left(\frac{\sum_{s'} \pi_{rs'} \hat{\pi}_{rs'} W_{s'} \hat{A}_{s'} \left(\frac{\sum_{r'} \pi_{r's} \hat{\pi}_{r's}}{\sum_{r'} \pi_{r's}} \right)^{\alpha-1}}{\sum_{s'} \pi_{rs'} W_{s'}} \right)^{\psi} \right)^{\frac{-\epsilon(1-\zeta)}{1+\psi}} \right)^{\frac{1+\psi}{\epsilon[(1+\psi)-\alpha(1+\zeta\psi)]}}$$

Simulating counterfactuals

An equilibrium is a fixed points in wages, housing prices, and commuting flows (in a closed economy). I use the algorithm below with an adaptive updating weight to find the a new equilibrium after a shock. I first simulate the closed economy counterfactual, then use that solution as the initial for the open economy counterfactual, if required:

1. Make an initial guess of wages and housing prices: $\{\hat{W}_i^{(0)}\}$, $\{\hat{Q}_i^{(0)}\}$. It is useful to set these equal to 1. Set the initial updating weight $\xi^{(0)} \in (0, 1)$ (typically I use 0.8).
2. Calculate $\{\hat{\pi}_{ij}^{(0)}\}$ using $\{\hat{W}_i^{(0)}\}$, $\{\hat{Q}_i^{(0)}\}$, and $\{\pi_{ij}\}$.
3. Main Loop:
   (a) Calculate $\{\hat{Q}_i^{(temp)}\}$ using $\{\hat{W}_i^{(t-1)}\}$, $\{W_i\}$, $\{\hat{\pi}_{ij}^{(t-1)}\}$, and $\{\pi_{ij}\}$.
   (b) Calculate $\{\hat{W}_i^{(temp)}\}$ using $\{\hat{\pi}_{ij}^{(t-1)}\}$, and $\{\pi_{ij}\}$.
   (c) Calculate $\{\hat{\pi}_{ij}^{(temp)}\}$ using $\{\hat{W}_i^{(t)}\}$, $\{\hat{Q}_i^{(t)}\}$, and $\{\pi_{ij}\}$.

(d) Update $\hat{X}^{(t)} = \xi^{(t)}\hat{X}^{(temp)} + (1-\xi^{(t)})\hat{X}^{(t-1)}$ for $\hat{X} \in \{\hat{Q}, \hat{W}, \hat{\pi}\}$, where ξ is a weight that disciplines updating.

(e) Calculate movement as (with $\mathcal{N}$ the number of pairwise observations):

$$\Delta^{(t)} = \frac{1}{\mathcal{N}} \sum_r \sum_s |\hat{\pi}_{rs}^{(t)} - \hat{\pi}_{rs}^{(t-1)}|.$$

(f) If $\Delta^{(t)} \geq \Delta^{(t-1)}$, set a new $\xi^{(t+1)} < \xi^{(t)}$.

(g) Stop when movement is below convergence criterion.

4. Initial guess for $\hat{\bar{N}}^{(0)}$ using $\{\hat{W}_i^{(temp)}\}$, $\{W_i\}$, $\{\hat{Q}_i^{(temp)}\}$, $\{\hat{\pi}_{ij}^{(temp)}\}$, and $\{\pi_{ij}\}$, resetting $\xi^{(0)}$.

5. Main Loop:

(a) Calculate $\{\hat{Q}_i^{(temp)}\}$ using $\hat{\bar{N}}^{(t-1)}$, $\{\hat{W}_i^{(t-1)}\}$, $\{W_i\}$, $\{\hat{\pi}_{ij}^{(t-1)}\}$, and $\{\pi_{ij}\}$.

(b) Calculate $\{\hat{W}_i^{(temp)}\}$ using $\hat{\bar{N}}^{(t-1)}$, $\{\hat{\pi}_{ij}^{(t-1)}\}$, and $\{\pi_{ij}\}$.

(c) Calculate $\{\hat{\pi}_{ij}^{(temp)}\}$ using $\{\hat{W}_i^{(t)}\}$, $\{\hat{Q}_i^{(t)}\}$, and $\{\pi_{ij}\}$.

(d) Calculate $\hat{\bar{N}}^{(temp)}$ using $\{\hat{W}_i^{(t)}\}$, $\{W_i\}$, $\{\hat{Q}_i^{(t)}\}$, $\{\hat{\pi}_{ij}^{(t)}\}$, and $\{\pi_{ij}\}$.

(e) Update $\hat{X}^{(t)} = \xi^{(t)}\hat{X}^{(temp)} + (1-\xi^{(t)})\hat{X}^{(t-1)}$ for $\hat{X} \in \{\hat{Q}, \hat{W}, \hat{\pi}, \hat{\bar{N}}\}$, where ξ is a weight that disciplines updating.

(f) Calculate movement as:

$$\Delta = \frac{1}{\mathcal{N}} \sum_r \sum_s |\hat{\pi}_{rs}^{(t)} - \hat{\pi}_{rs}^{(t-1)}|.$$

(g) If $\Delta^{(t)} \geq \Delta^{(t-1)}$, set a new $\xi^{(t+1)} < \xi^{(t)}$.

(h) Stop when movement is below convergence criterion.

With Agglomeration

When modeling agglomeration, I use the following system:

$$\hat{\Upsilon}_i = \frac{\sum_n e^{\delta_A d_{in}} \sum_r \pi_{rn}\hat{\pi}_{rn}}{\sum_n e^{\delta_A d_{in}} \sum_r \pi_{rn}}$$

$$\hat{\Omega}_i = \frac{\sum_n e^{\delta_B d_{ni}} \sum_s \pi_{ns}\hat{\pi}_{ns}}{\sum_n e^{\delta_B d_{ni}} \sum_s \pi_{ns}}$$

$$\hat{W}_i = \hat{A}_i \hat{\Upsilon}_i^{\mu} \hat{\bar{N}}^{\alpha-1} \left(\frac{\sum_r \pi_{ri}\hat{\pi}_{ri}}{\sum_r \pi_{ri}}\right)^{\alpha-1}$$

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

$$\hat{\pi}_{ij} = \frac{\hat{B}_i \hat{E}_j \hat{D}_{ij} \hat{W}_j^{\epsilon} \hat{Q}_i^{-\epsilon(1-\zeta)} \hat{\Omega}_i^{\eta}}{\sum_r \sum_s \pi_{rs} \hat{B}_r \hat{E}_s \hat{D}_{rs} \hat{W}_s^{\epsilon} \hat{Q}_r^{-\epsilon(1-\zeta)} \hat{\Omega}_r^{\eta}}$$

E.2 Additional Counterfactual Exercises

Appendix Table H12 presents a variety of additional model results. I describe them here. The table contains three columns, reflecting partial equilibrium, general equilibrium, and general equilibrium with spillovers. The general equilibrium with and without spillovers are as presented in the main text and in these appendices.

The partial equilibrium results are calculated in a different manner. Rather than being the result of a fixed point algorithm, these are akin to only initializing the first round of fixed point process. That is, for Equations (E1)–(E2), let wages and housing prices reflect just the changes in fundamentals

$$\hat{A} \rightarrow \hat{W}$$
$$\hat{C} \rightarrow \hat{Q}$$

Next, feed the changes in $\hat{B}$, $\hat{D}$, and $\hat{E}$ into the following variant of Equation (E3), which ignores the price changes:

$$\hat{\pi}_{ij} = \frac{\hat{B}_i \hat{E}_j \hat{D}_{ij}}{\sum_r \sum_s \pi_{rs} \hat{B}_r \hat{E}_s \hat{D}_{rs}}$$

Then, feed the updated prices and $\hat{\pi}$ vector into the welfare formula:

$$\ln \hat{\bar{U}} = \frac{1}{\epsilon} \ln \left(\frac{\hat{B}_i \hat{E}_j \hat{D}_{ij} \hat{W}_j^{\epsilon} \hat{Q}_i^{-\epsilon(1-\zeta)}}{\hat{\pi}_{ij}} \right)$$

Thus, this partial equilibrium effect accounts for mobility induced changes to B, D, and E, and changes to utility induced by changes in wage or housing prices (only because of changes in A and C), but does not reflect mobility induced by changes in prices or changes in prices induced by mobility.

The first panel of Appendix Table H12 corresponds to the results presented in the main text. The second panel assumes a $\hat{C}$ just in tracts that contain a transit stations such that the partial equilibrium effect results a 10% higher residential population in those tracts (allowing $\hat{C} \rightarrow \hat{Q} \rightarrow \hat{\pi}$). The third panel assumes that $\lambda^B = 0.05$ using the 500m measure of treatment proximity. The fourth panel assumes that $\lambda^A = 0.04$ using the 500m measure of treatment proximity.

Combining historic and future counterfactuals

All of the main counterfactual simulations presented in Table 7 except the dynamic 2015 effects are *historic* in nature: by how much would the region be worse off if LA Metro Rail were removed, relative to observed outcomes in 2000. The dynamic 2015 effect takes that as given and instead asks additionally about the *future*: by how much is the region better off assuming commuting growth through 2015, relative to the observed data in 2000 (which includes the transit system as built). The bottom three panels of Appendix Table H12 all assume that the additional effects are *future* effects, taking place after 2000.

E.3 Bootstrapping Procedure

To my knowledge, no off-the-shelf bootstrapping procedure works well for developing joint bootstrap estimates of the parameters of the model presented in Equations (12)–(14). A central challenge is the need to preserve the correlation structure of parameters estimated across these equations. This, in turn, is complicated by the use of both IV to estimate some parameters, and the possible presence of dyadic correlation structures in the estimation of other parameters. This multiple-cluster case suffers from a potential degeneracy issue that renders standard bootstrapping approaches for dyadic data, such as the pigeonhole bootstrap (Owen 2007), as overly conservative (Davezies, D'Haultfœuille, and Guyonvarch 2019; Menzel 2020). Fortunately, recent research offers bootstrapping procedures that produce more accurate confidence intervals for IV and for dyadic data under some additional assumptions (Davidson and MacKinnon 2010; Davezies, D'Haultfœuille, and Guyonvarch 2019; Menzel 2020). For an overview of inference under multiple clusters and networks more generally, see Graham (2020).

I therefore describe a hybrid wild bootstrap procedure that combines recent results on bootstrapping under multi-way error structures by Menzel (2020) and the wild restricted efficient residual bootstrap for IV by Davidson and MacKinnon (2010). There are two key features of this approach. Foremost and *essentially*, the same sets of bootstrapping weights are used across equations, so this procedure captures the correlation of estimates across equations. This is vital for correct model inference. Second, the approach used for each equation is relatively efficient.[E.1]

A central challenge is bootstrapping the dyadic estimating equation in a way the reflects the three-way cluster error structure implemented in the paper. Experimentation revealed that both the pigeonhole bootstrap (Owen 2007) and the related method presented in Davezies, D'Haultfœuille, and Guyonvarch (2019) are much more conservative than the three-way cluster. There is likely a good reason: the bootstrap can fail in degenerate settings, such as if errors are approximately iid (Davezies, D'Haultfœuille, and Guyonvarch 2019; Graham 2020; Menzel 2020). Such degeneracy is quite likely conditional on rich sets of fixed effects (Menzel 2020).

Modern techniques rely on the correspondence of dyadic data to exchangeable arrays (Davezies, D'Haultfœuille, and Guyonvarch 2019). Menzel (2020) suggests a solution in the degenerate case.[E.2] In the particular case of an additive regression model with homoskedastic errors (which is not unlikely conditional on fixed effects), a double differencing approach has excellent convergence properties, but has a non-standard limiting distribution. However, he develops a bootstrap procedure that approximates the limiting distribution. This is a form of wild bootstrap that uses a convolution of two Gamma-distributed random variables to form bootstrap residuals. The convolution Each weight corresponds to 'one dimension' of the dyadic data, and so can naturally be used as the wild bootstrap weight for non-dyadic estimating equations. Those are IV estimators, so I turn to the wild restricted efficient residual bootstrap by Davidson and MacKinnon (2010), but use the same Gamma-distributed weights as used for the dyadic data.

In order fit my research design into the double-differencing framework of Menzel (2020), I first take differences of Equation (2); this implicitly controls for autocorrelation with origin-destination pair (see Davezies, D'Haultfœuille, and Guyonvarch 2019, for a similar first step). Let $\Delta\ddot{x}_{ijt}$ denote the double-differenced value of Δx_{ijt} with respect to i and j, where $\Delta x_{ijt} = x_{ij,t=1} - x_{ij,t=0}$. That

E.1. Note that the procedure developed here allows for correlation within $\{i,j\}$ pairs over time, across pairs $\{i,j\}$ and $\{i,j'\}$ for $j' \neq j$, across pairs $\{i,j\}$ and $\{i',j\}$ for $i' \neq i$, but does not allow correlation between $\{i,j\}$ and $\{j',i\}$, even for $j = j'$. How to handle this case is an active area of research; see Graham (2020) for more discussion.

E.2. Menzel (2020) also offers a more sophisticated adaptive bootstrap procedure.

is,

$$\Delta\ddot{x}_{ijt} = \Delta x_{ijt} - \bar{\Delta x}_{iJt} - \bar{\Delta x}_{Ijt} + \bar{\Delta x}_{IJt}$$

where $\bar{\Delta x}_{iJt} = J^{-1}\sum_j \Delta x_{ijt}$, $\bar{\Delta x}_{Ijt} = I^{-1}\sum_i \Delta x_{ijt}$, and $\bar{\Delta x}_{IJt} = (I \times J)^{-1}\sum_i\sum_j \Delta x_{ijt}$ are one- and two-way averages.

The estimating equations for the bootstrap be:

$$\Delta\ddot{n}_{ijt} = \Delta\ddot{T}_{ijt}\lambda + \Delta\ddot{d}_{ijt} \tag{D1}$$

$$\Delta\Omega_{jt} = \epsilon\Delta w_{jt} + \Delta e_{jt} \tag{D2.IV}$$

$$\Delta w_{jt} = \pi_\epsilon \Delta z_{jt} + \Delta u_{\epsilon,jt} \tag{D2.1st}$$

$$\Delta q_{it} = \psi\Delta h_{it} + \Delta c_{it} \tag{D3.IV}$$

$$\Delta h_{it} = \pi_\psi \Delta z_{it}^{HD,a}(\rho) + \Delta u_{\psi,it} \tag{D3.1st}$$

where I've omitting covariates or subcounty and subcounty-pair fixed effects for parsimony, let $\lambda = \lambda^D$, and assumed that Ω_{jt} is fixed. The bootstrapping procedure below applies the same set of wild bootstrap residual weights to create estimates using the method of Menzel (2020) for Equation (D1) and Davidson and MacKinnon (2010) for the two sets of IV equations in (D2) and (D3).

Note that Equations (D2) and (D3) are precisely identical to those presented in the paper. Equation (D1) is estimated in a slightly different way than that in the paper, in that it does not use iterative demeaning (instead employing the double difference). Therefore, point estimates are slightly different. These are presented in Table E1. While I provide results from the full and PER samples for comparison, I rely on the Immediate 1925 Plan Sample for the bootstrap procedure. Because the coefficient on "O & D <500m from station" is close to zero and insignificant, I do not use it in welfare simulations (instead setting it equal to 0).

Table E1: Effect of Transit on Commuting Flows by 2000 (time differenced then double differenced)

	(1)	(2)	(3)
O & D contain station	0.088**	0.098**	0.134**
	(0.039)	(0.045)	(0.058)
O & D <250m from station	0.048	0.079	0.115*
	(0.047)	(0.051)	(0.061)
O & D <500m from station	-0.022	0.009	0.004
	(0.036)	(0.039)	(0.049)
N	145555	49740	9611
Control Group	All	PER	Immed. '25 Plan
Standard Three-Way FEs	Y	Y	Y
Subcounty Pair-×-Year FEs	Y	Y	Y
Highway Controls	Y	Y	Y

Standard errors clustered by tract pair, tract of residence, and tract of work in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Bootstrap Routine

The bootstrap implemented in the paper takes as fixed ζ and α, assigns λ^D under distance iii) (O&D<500m from station) equal to zero, assigns $\lambda^A = \lambda^B = 0$ consistent with empirical results, and maintains the assumption that $\lambda^C = \lambda^E = 0$. The bootstrapped input parameters are ϵ, ψ, and $\lambda^{D'}$ under distance i) and ii). I use $\mathcal{B} = 400$ wild bootstrap draws.

1. Separately estimate Equations D1, D2, and D3 as above, using IV for Equations D2 and D3. Recover parameter estimates $\tilde{\lambda}$, $\tilde{\epsilon}$, and $\tilde{\psi}$; as well as residual estimates $\Delta\hat{\ddot{d}}_{ijt}$.

2. Estimate the equations below using OLS while enforcing the identified coefficients $\tilde{\epsilon}$ and $\tilde{\psi}$, then recover the residuals $\Delta\hat{e}_{jt}$ and $\Delta\hat{c}_{it}$:

$$\Delta\Omega_{jt} - \tilde{\epsilon}\Delta w_{jt} = \text{covariates} + \Delta e_{jt}$$
$$\Delta q_{it} - \tilde{\psi}\Delta h_{it} = \text{covariates} + \Delta c_{it}$$

3. Because the second stage residuals in Equations D2.1st and D3.1st do not reflect correlation with $\Delta\hat{e}_{jt}$ and $\Delta\hat{c}_{it}$, using them to create the bootstrap sample is inefficient. Instead, separately estimate:

$$\Delta w_{jt} = \pi_\epsilon \Delta z_{jt} + \varpi_\epsilon \Delta\hat{e}_{jt} + \Delta o_{\epsilon,jt}$$
$$\Delta h_{it} = \pi_\psi \Delta z_{it}^{HD,a}(\rho) + \varpi_\psi \Delta\hat{c}_{it} + \Delta o_{\psi,it}$$

   and then save the estimates $\hat{\pi}_\epsilon$ and $\hat{\pi}_\psi$, then generate first stage residuals incorporating the predicted contribution of the second stage correlation to the estimated residuals as follows:

$$\Delta\hat{u}_{\epsilon,jt} \equiv \hat{\varpi}_\epsilon \Delta\hat{e}_{jt} + \Delta\hat{o}_{\epsilon,jt}$$
$$\Delta\hat{u}_{\psi,it} \equiv \hat{\varpi}_\psi \Delta\hat{c}_{it} + \Delta\hat{o}_{\psi,it}$$

4. Draw $\tilde{\mathcal{B}} = \mathcal{B} * 1.025$ sets of $2\mathcal{N}$ iid random variables from a Gamma distribution with shape parameter 4 and scale parameter 1/2, and subtract 2 from these values (such that these variables are mean 0, variance 1, and skewness 1). For each set of random variables $b \in 1, \ldots, \tilde{\mathcal{B}}$, index elements in the first half by $i \in 1, \ldots, \mathcal{N}$ and in the second half by $j \in 1, \ldots, \mathcal{N}$, so that, e.g., ω_{b_i} is the bootstrap weight for correspond to location i in bootstrap sample b.

5. Generate bootstrap samples and recover bootstrap estimates. That is, for each b:

   (a) Create bootstrap residual values as follows:

$$\Delta\hat{\ddot{d}}^*_{ijt} \equiv \omega_{b_i} \cdot \omega_{b_j} \cdot \Delta\hat{\ddot{d}}_{ijt}$$
$$\Delta\hat{e}^*_{jt} \equiv k^*_\epsilon \cdot \omega_{b_j} \cdot \Delta\hat{e}_{jt}$$
$$\Delta\hat{u}^*_{\epsilon,jt} \equiv l^*_\epsilon \cdot \omega_{b_j} \cdot \Delta\hat{u}_{\epsilon,jt}$$
$$\Delta\hat{c}^*_{it} \equiv k^*_\psi \cdot \omega_{b_i} \cdot \Delta\hat{c}_{it}$$
$$\Delta\hat{u}^*_{\psi,jt} \equiv k^*_\psi \cdot \omega_{b_i} \cdot \Delta\hat{u}_{\psi,jt}$$

where $k^* = (\mathcal{N}/(\mathcal{N}-k))^{1/2}$ and $l^* = (\mathcal{N}/(\mathcal{N}-l))^{1/2}$ are scale adjustments wherein the denominators are the residual degrees of freedom for the uninstrumented and instrumented equations, respectively.

(b) Create the bootstrap sample as follows, where Equations SMP.3 and SMP.5 are respectively defined before SMP.2 and SMP.4:

$$\Delta\hat{\ddot{n}}^*_{ijt} \equiv \Delta\ddot{T}_{ijt}\tilde{\lambda} + \Delta\hat{\ddot{d}}^*_{ijt} \tag{SMP.1}$$

$$\Delta\hat{\Omega}^*_{jt} \equiv \tilde{\epsilon}\Delta\hat{w}^*_{jt} + \Delta\hat{e}^*_{jt} \tag{SMP.2}$$

$$\Delta\hat{w}^*_{jt} \equiv \hat{\pi}_\epsilon\Delta z_{jt} + \Delta\hat{u}^*_{\epsilon,jt} \tag{SMP.3}$$

$$\Delta\hat{q}^*_{it} \equiv \tilde{\psi}\Delta\hat{h}^*_{it} + \Delta\hat{c}^*_{it} \tag{SMP.4}$$

$$\Delta\hat{h}^*_{it} \equiv \hat{\pi}_\psi\Delta z^{HD,a}_{it}(\rho) + \Delta\hat{u}^*_{\psi,it} \tag{SMP.5}$$

(c) Separately estimate Equations BS1, BS2, and BS3 as below, using IV for equation BS2 and BS3. Save bootstrap estimates $\{\lambda^*, \epsilon^*, \psi^*\}_b$.

$$\Delta\hat{\ddot{n}}^*_{ijt} = \Delta\ddot{T}_{ijt}\lambda^* + \Delta\ddot{d}^*_{ijt} \tag{BS1}$$

$$\Delta\hat{\Omega}^*_{jt} = \epsilon^*\Delta\hat{w}^*_{jt} + \Delta e^*_{jt} \tag{BS2.IV}$$

$$\Delta\hat{w}^*_{jt} = \pi^*_\epsilon\Delta z_{jt} + \Delta u^*_{\epsilon,jt} \tag{BS2.1st}$$

$$\Delta\hat{q}^*_{it} = \psi^*\Delta\hat{h}^*_{it} + \Delta c^*_{it} \tag{BS3.IV}$$

$$\Delta\hat{h}^*_{it} = \pi^*_\psi\Delta z^{HD,a}_{it}(\rho) + \Delta u^*_{\psi,it} \tag{BS3.1st}$$

6. Remove any sets b of bootstrap estimates for which $\epsilon^* < 0$ or $\psi^* < 0$. Randomly sample from the remaining sets of bootstrap estimates to ensure $\mathcal{B}$ replicates.

7. For each set of bootstrap estimates, simulate the model using $\{\lambda^*, \epsilon^*, \psi^*\}_b$ to create a bootstrapped welfare estimate $\mathcal{W}^*_b$

8. Report the 95% central CI discarding the tails of $\mathcal{W}^*_b, \forall b$.

F Gravity and Commuting Costs

First, a note on measures of travel time/cost:

- τ^{GIS}: Network travel times are calculated from route-querying software. These are *only available in the cross-section*, but are available for every origin-destination pair.
- τ^{Obs}: Observed travel times come from the CTPP. They are *panel data*, but only available between pairs with positive commuting that satisfy disclosure requirements.

I calculate gravity comparing both of these measure and several techniques. The availability of panel data creates a challenge for gravity models using cross-sectional measures of travel time: There is no time variation, and so time-invariant pair fixed effect absorb all variation in travel times, and κ cannot be identified.

To illustrate, Table F1 reports estimates of $\epsilon\kappa$ from the following models, with and without pair fixed effects

$$n_{ijt} = \omega_{jt} + \theta_{it} - \epsilon\kappa\tau_{ijt}^{\text{Obs}} + \lambda^{D'} T_{ijt} + \ln(D_{ijt})$$
$$n_{ijt} = \omega_{jt} + \theta_{it} - \epsilon\kappa\tau_{ijt}^{\text{Obs}} + \lambda^{D'} T_{ijt} + \varsigma_{ij}^{D} + \ln(D_{ijt})$$

Without pair fixed effects, the elasticity of commuting with respect to travel time is -0.41 (in column 1), substantially smaller in magnitude than the -1 sometimes used in trade. In comparison, including pair fixed effects generates an estimate of 0.07, indicating that small increases in travel time may actually increase commuting. This captures the tricky issue with using panel data for measuring gravity: For tract pairs that see increases in commuting, congestion may increase, causing increases in travel time (and reverse causality). However it is striking that the sign switches.

Observed travel times in the census are averages of recalled times across all commuters, and may be subject to measurement error. How bad might this measurement error be? For comparison, column (3) reports the results from:

$$n_{ijt} = \omega_{jt} + \theta_{it} - \epsilon\kappa\tau_{ij}^{\text{GIS}} + \lambda^{D'} T_{ijt} + \ln(D_{ijt})$$

using the GIS-calculated measure of travel time. It is about 50% larger in magnitude than column 1. This indicates that there is measurement error, but also that observed travel times likely contain substantial signal.

An ideal approach would control for time-invariant determinants of commuting between pairs, but still allow recovering the elasticity of commuting. I propose a two-step approach, first recovering estimates of ς_{ij}^{D} from above then regressing them on a measure of time:

$$\hat{\varsigma}_{ijt}^{D} = -\epsilon\kappa\tau_{ijt}^{\text{Obs}} + u_{ijt}$$
$$\hat{\varsigma}_{ij}^{D} = -\epsilon\kappa\tau_{ij}^{\text{GIS}} + u_{ij}$$

where $\hat{\varsigma}_{ij0}^{D} = \hat{\varsigma}_{ij1}^{D}$ in the first model. Note that, unlike for the ω and θ fixed effects, it is unreasonable to assume asymptotic arguments as the pair fixed effects are estimated from a short panel. This means there may be large measurement error $\hat{\varsigma}_{ij}^{D}$, although expanding the time dimension of the panel likely improves this margin.

Columns 4–7 show the results of the second stage of this two step process. In columns 4–5, $\hat{\varsigma}_{ij}^{D}$ are estimates from a log-linear model, while in columns 6–7, $\hat{\varsigma}_{ij}^{D}$ are estimates from a PPML model. Note that the coefficients on observed and GIS-calculated measures of travel time are roughly similar now. The log-linear first step results are also a bit smaller than the PPML first step results.

Table F1: Measuring Gravity in the Panel

	n_{ijt}			$\hat{\varsigma}_{ij}^{D}$ (Two-Step Estimator)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(\tau_{ijt}^{\text{Obs}})$	-0.414***	0.073***		-0.239***		-0.391***	
	(0.010)	(0.005)		(0.012)		(0.011)	
$\ln(\tau_{ij}^{\text{GIS}})$			-0.600***		-0.257***		-0.368***
			(0.013)		(0.014)		(0.012)
N	717073	276128	771999	282757	143353	726261	628129
Origin- & Destination-by-Year FEs	Y	Y	Y	na	na	na	na
Pair FEs	-	Y	-	na	na	na	na
First Step Estimated by:	na	na	na	Lin.	Lin.	PPML	PPML

Estimates of marginal disutility of travel time; outcome is log commuting flow in columns 1–3, and pair FEs derived from gravity in columns 4–7. Standard errors clustered by tract pair (columns 1, 2, 3, 4, 6), tract of residence (all columns), and tract of work (all columns) in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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H Additional and Supplementary Results

Summary of Additional Results

- Figure H1: LA Metro Rail Ridership, 1990-2000
- Figure H2: LA Metro Rail Ridership, 1990-2014
- Figure H3: Glossary of variables and parameters
- Figure H4: Timeline of transportation in Los Angeles
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- Table H1: Pre-trends in tract-level characteristics, 1970-1990
- Table H2: Treatment is not related to changes in zero flows or years opened
- Table H3: Effect of transit on commuting flows by 2000 (PPML with HDFEs)
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- Table H8: Transit and non-commuting fundamentals with half spatial decay
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- Table H11: Effect of LA Metro Rail on Residential Commute Share using Rail Transit
- Table H12: Welfare effects of model extensions (% change in welfare)

Appendix Figures and Tables

Figure H1: LA Metro Rail Ridership, 1990-2000

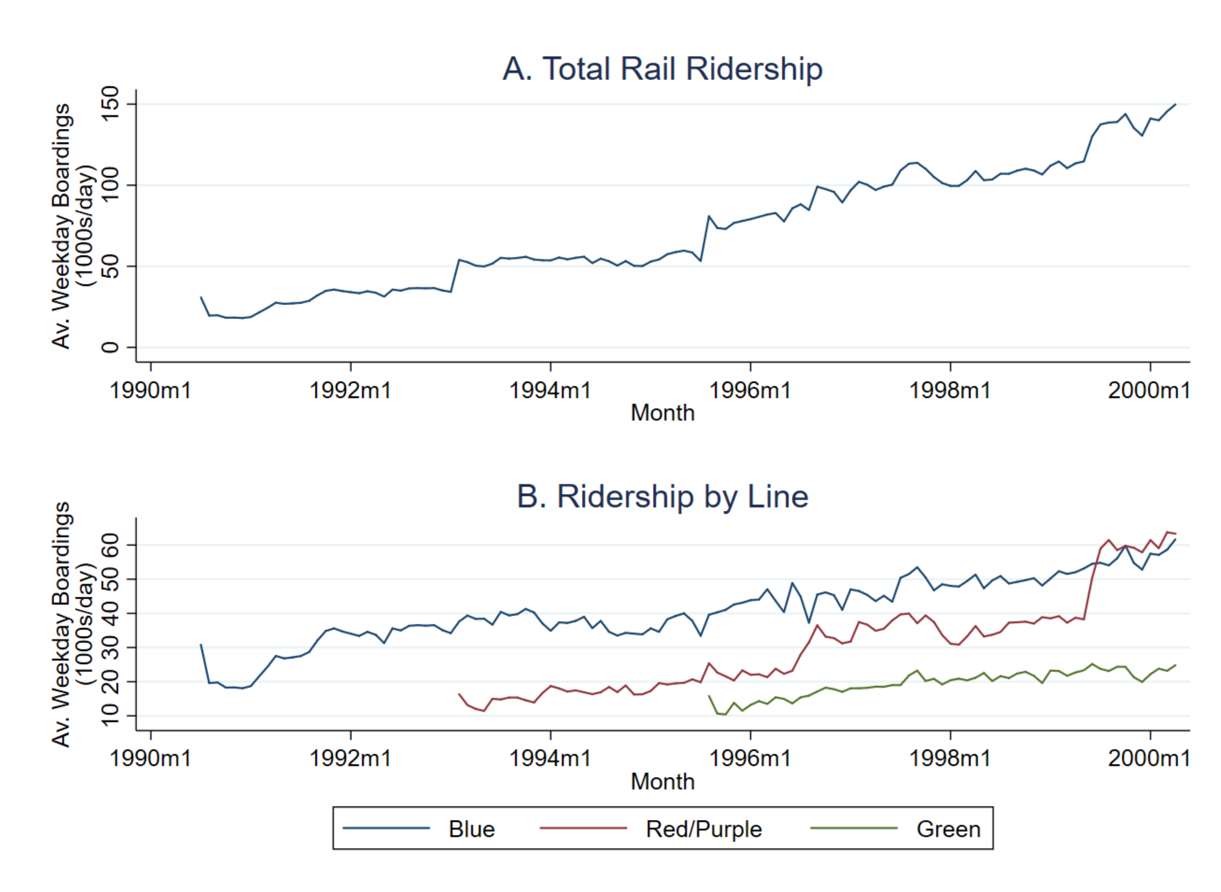


Figure H2: LA Metro Rail Ridership, 1990-2014

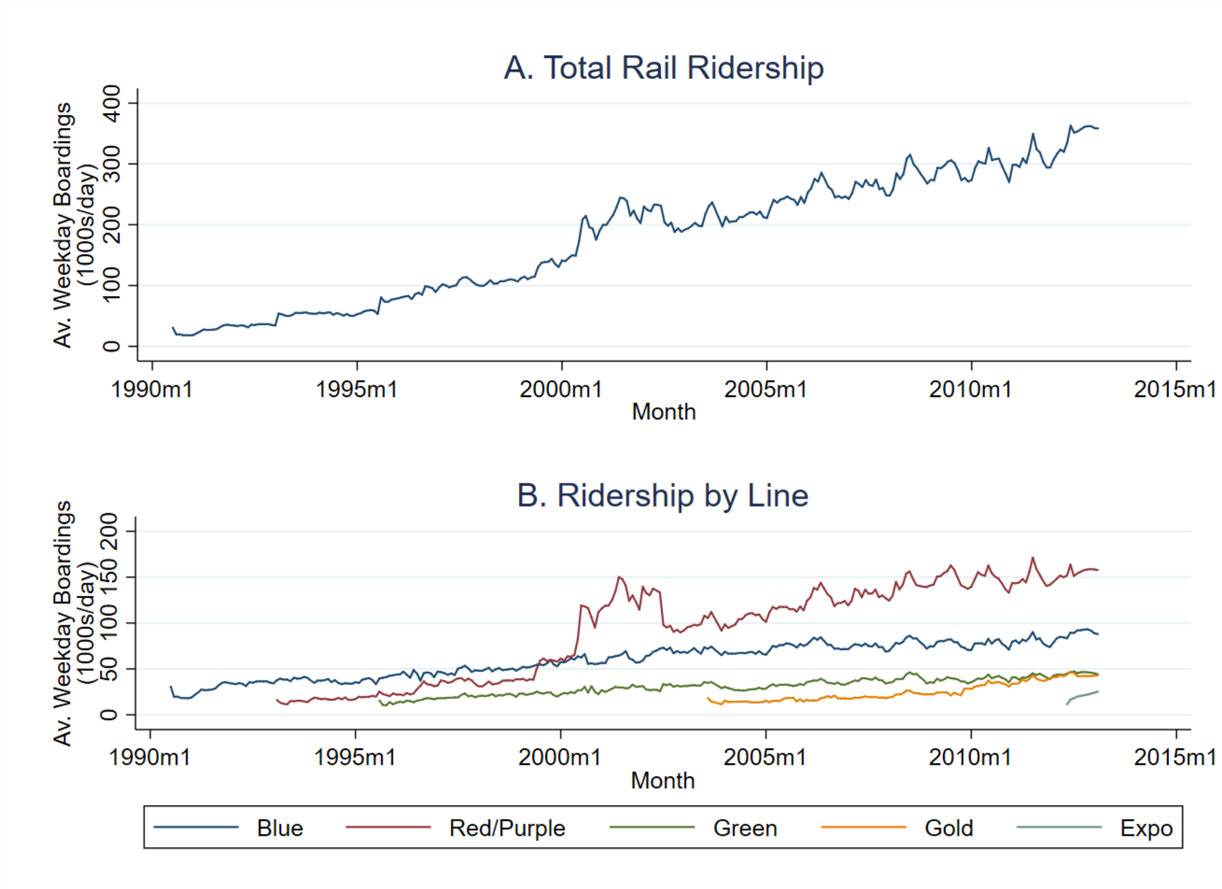


Figure H3: Glossary of variables and parameters

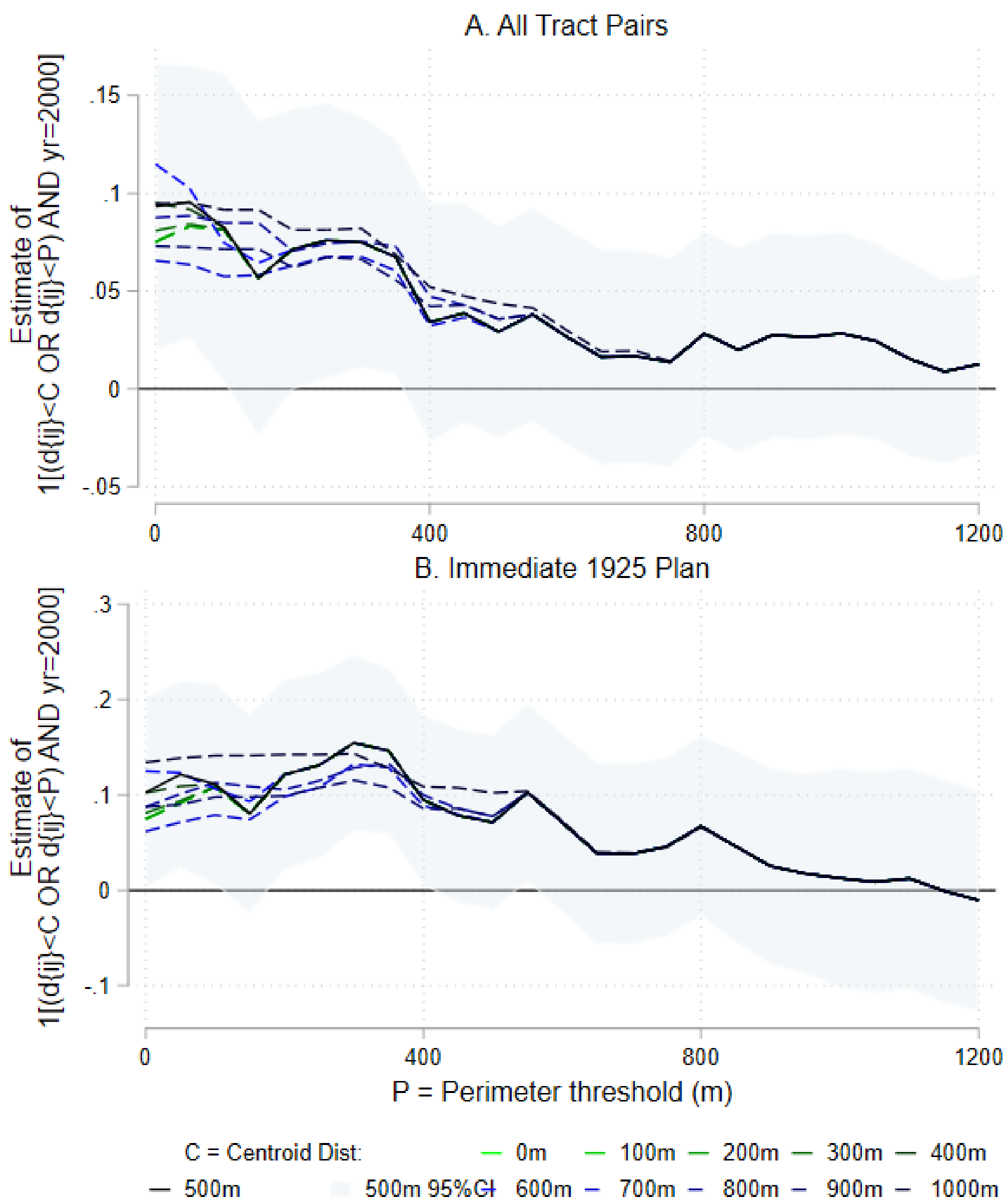
Parameters	Interpretation
ϵ	Homogeneity of location preferences (and wage elasticity of labor supply)
ζ	Household expenditure share on non-housing goods
$\tilde{\zeta} = -\epsilon(1-\zeta)$	Price elasticity of housing demand
α	Share of (production) income spent on labor
$\tilde{\alpha} = \alpha - 1$	Inverse wage elasticity of labor demand
ϕ	Share of housing income spent on land
$\tilde{\psi}$	Congestive cost of housing
$\psi = \tilde{\psi}\phi$	Inverse price elasticity of housing supply
κ	Semi-elasticity of commuting with respect to travel time
ρ	Spatial decay for instrumental variable construction
λ^x	Treatment effect for outcome x

Variables	Interpretation
A	Workplace productivity
$B = T\tilde{B}^{\epsilon}$	Gross residential amenity
$\tilde{B}$	Simple residential amenity
T	Mean residential utility
C	Inverse housing efficiency
$\tilde{C}$	Housing productivity
D	Mean utility commute (net of time)
E	Workplace amenity (net of wage)
$\mathcal{C}$	Consumption
H	Housing quantity
W	Wage
Q	Housing price
$\delta = e^{\kappa\tau}$	Commuting friction
τ	Travel time
π	Commuting share
$\bar{N}$	Aggregate population
N^Y	Employment at place of work
L^Y	Land used for production
M	Housing materials
L^H	Land used for housing
P^M	Price of housing materials
$P^L = (H/L^H)^{\psi}$	Price of land

Figure H4: Timeline of transportation in Los Angeles

1925	Comprehensive Rapid Transit Plan for the County of Los Angeles, Kelker, De Leuw & Co. developed at the request of local governments
1951	Los Angeles Metropolitan Transit Authority (LAMTA) formed
1961	Pacific Electric (Red Cars) end of service
1963	Los Angeles Railway (Yellow Cars) end of service
1964	Southern California Rapid Transit District (SCRTD) formed from LAMTA
3/24/1985	Ross Dress for Less methane explosion in Wilshire-Fairfax
1985	Construction begins on LA Metro Rail
11/20/1985	Department of Transportation and Related Agencies Appropriation Act (1986) includes language prohibiting funding of tunnels for transit along Wilshire corridor due to concerns about methane (HR 3244)
7/14/1990	Blue Line opens
2/15/1991	Metro Center station opens
1993	Los Angeles County Metropolitan Transportation Authority forms from SCRTD
1/30/1993	Red Line opens, connects system to Union Station
10/14/1993	Century Freeway (I-105) opens
8/12/1995	Green Line opens in median of Century Freeway
7/13/1996	Red Line expands to Wilshire/Vermont
6/12/1999	Red Line expands to Hollywood/Vine
6/24/2000	Red Line expands to North Hollywood
7/26/2003	Gold Line opens
2006	Purple Line renamed from Red Line branch
9/20/2006	HR 3244 amended to remove prohibitions on funding of tunnels for transit along Wilshire corridor
11/15/2009	Gold Line expands in East LA
4–6/2012	Expo Line opens
3/5/2016	Gold Line expands to Azusa
5/20/2016	Expo Line expands to Santa Monica

Figure H5: Robustness to different distance bin assumptions



Effect of a single treatment under various definitions of i) as estimated by Equation (2). P represents the distance from a station exterior a tract to the perimeter and is zero if the tract contains a station; in the main text it is zero. C represents the second criterion of i) in the main text, the limiting centroid distance; it is 500m in the main text.

Table H1: Pre-trends in tract-level characteristics, 1970-1990

	Model-relevant				Other characteristics			Travel characteristics		
	ln Res. Emp. (1)	ln #HHs (2)	ln HHI (3)	ln House Value (4)	% Coll. Grads (5)	Pov. Rate (6)	% Moved <5yrs (7)	%HHs No Car (8)	%Com. Use Auto (9)	%Com. Use Transit (10)
All Tracts										
$\text{Proximity}_i^{500m} \times t$	0.025	-0.032*	-0.015	-0.023	-0.015***	0.015***	-0.016***	-0.015***	0.004	0.012***
	(0.020)	(0.016)	(0.012)	(0.014)	(0.003)	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)
N	11643	11632	11556	11383	11650	11651	11651	7774	11644	11644
PER Sample										
$\text{Proximity}_i^{500m} \times t$	0.003	-0.036**	-0.015	-0.042***	-0.015***	0.012***	-0.014**	-0.014**	0.004	0.012***
	(0.022)	(0.017)	(0.014)	(0.016)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)	(0.004)
N	3696	3695	3689	3591	3696	3696	3696	2464	3696	3696
Full 1925 Plan Sample										
$\text{Proximity}_i^{500m} \times t$	-0.003	-0.032*	-0.018	-0.023	-0.011***	0.010**	-0.012**	-0.010	0.006	0.008*
	(0.021)	(0.017)	(0.013)	(0.016)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
N	2886	2886	2881	2788	2886	2886	2886	1924	2886	2886
Immediate 1925 Plan Sample										
$\text{Proximity}_i^{500m} \times t$	0.023	-0.010	-0.015	-0.004	-0.007*	0.007	-0.007	-0.010	0.006	0.011**
	(0.021)	(0.019)	(0.015)	(0.019)	(0.004)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
N	1236	1236	1236	1158	1236	1236	1236	824	1236	1236
Subcounty-×-Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Estimates show pre-trends from 1970-1990 for tracts treated between 1990-1999, except Column (8), which only covers 1980-1990. HH is households, and HHI is household income. Data are from the Neighborhood Change Database and reflect 2010 geographies. All regressions include tract and subcounty-by-year fixed effects. Standard errors clustered by tract in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H2: Treatment is not related to changes in zero flows or years opened

	$1_{N_{ijt}>0}$			$\ln(N_{ijt})$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
O & D contain station	0.015	0.008	0.005	0.185***	0.150**	0.098**	0.167**	0.142**
	(0.034)	(0.031)	(0.038)	(0.061)	(0.058)	(0.040)	(0.082)	(0.059)
O & D <250m from station	0.005	0.000	-0.026	0.148**	0.105*	0.058	0.145*	0.128**
	(0.027)	(0.026)	(0.033)	(0.061)	(0.058)	(0.046)	(0.077)	(0.065)
O & D <500m from station	0.052**	0.035	0.019	0.073	0.036	-0.009	0.030	0.013
	(0.024)	(0.022)	(0.027)	(0.058)	(0.053)	(0.035)	(0.071)	(0.052)
Years Open				0.073	0.036		0.030	
				(0.058)	(0.053)		(0.071)	
Years Open $\times$ O & D contain station						0.004		0.027*
						(0.013)		(0.015)
Years Open $\times$ O & D <250m from station						-0.010		-0.011
						(0.015)		(0.018)
Years Open $\times$ O & D <500m from station						-0.014		-0.012
						(0.010)		(0.013)
N	1263082	1262478	69614	291532	291110	291110	19222	19222
Control Group	All	All	Immed. '25 Plan	All	All	All	Immed. '25 Plan	Immed. '25 Plan
Standard Three-Way FEs	Y	Y	Y	Y	Y	Y	Y	Y
Subcounty Pair-$\times$-Year FEs	-	Y	Y	-	Y	Y	Y	Y
Highway Controls	-	Y	Y	-	Y	Y	Y	Y

High-dimensional fixed effects estimates of transit on an indicator for positive flows (Columns 1-3) or log commuting flow (Columns 4-8); standard three-way fixed effects are tract of work-by-year, tract of residence-by-year, and tract pair. Sample consists of all non-missing/singular tract pairs. Years opened is relative the newest station nearest either origin or destination, centered on 5 years (the mean value). Standard errors clustered by tract pair, tract of residence, and tract of work in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H3: Effect of Transit on Commuting Flows by 2000 (PPML with HDFEs)

	Full Sample			History & Shocks			Same Line	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
O & D contain station	0.135**	0.164**	0.125*	0.107	0.131*	0.163**	0.207*	0.152
	(0.069)	(0.074)	(0.065)	(0.068)	(0.068)	(0.081)	(0.123)	(0.125)
O & D <250m from station		0.135**	0.101	0.129*	0.122*	0.120	0.210**	0.158
		(0.067)	(0.062)	(0.067)	(0.068)	(0.079)	(0.093)	(0.103)
O & D <500m from station		0.129**	0.077	0.084*	0.071	0.063	0.096	0.101
		(0.058)	(0.049)	(0.050)	(0.051)	(0.057)	(0.070)	(0.077)
N	1261978	1261978	1259440	407832	310924	69596	26270	12172
Control Group	All	All	All	PER	Full '25 Plan	Immed. '25 Plan	Ever Treated	Treated by 2000
Standard Three-Way FEs	Y	Y	Y	Y	Y	Y	Y	Y
Subcounty Pair-×-Year FEs	-	-	Y	Y	Y	Y	Y	Y
Highway Controls	-	-	Y	Y	Y	Y	Y	Y

High-dimensional fixed effects estimates of λ^D with PPML estimator; standard three-way fixed effects are tract of work-by-year, tract of residence-by-year, and tract pair. Outcome is commuting flow. Treatment variables are mutually exclusive. Column titles define treatment: tracts pairs on any lines are treated in Columns (1)-(6), while only tract pairs on the same line are treated in Columns (7) and (8). Standard errors clustered by tract pair, tract of residence, and tract of work in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H4: Effects are larger for tract pairs on same line

	(1)	(2)	(3)	(4)	(5)	(6)
O & D contain station						
Same line	0.151***	0.163***	0.144***	0.153***	0.192***	0.205***
	(0.053)	(0.053)	(0.051)	(0.055)	(0.058)	(0.071)
Not same line	0.026	0.035	0.040	0.056	0.087	0.075
	(0.076)	(0.077)	(0.076)	(0.084)	(0.082)	(0.088)
O & D <250m from station						
Same line		0.094	0.064	0.096	0.115*	0.145**
		(0.058)	(0.060)	(0.062)	(0.062)	(0.071)
Not same line		0.046	0.049	0.087	0.095	0.105
		(0.059)	(0.059)	(0.062)	(0.064)	(0.079)
O & D <500m from station						
Same line		0.032	0.015	0.048	0.046	0.041
		(0.044)	(0.042)	(0.046)	(0.048)	(0.060)
Not same line		-0.069	-0.072	-0.037	-0.051	-0.048
		(0.046)	(0.044)	(0.046)	(0.046)	(0.056)
N	291532	291532	291110	99480	74408	19222
Control Group	All	All	All	PER	Full '25 Plan	Immed. '25 Plan
Standard Three-Way FEs	Y	Y	Y	Y	Y	Y
Subcounty Pair-×-Year FEs	-	-	Y	Y	Y	Y
Highway Controls	-	-	Y	Y	Y	Y

High-dimensional fixed effects estimates of λ^D with log-linear estimator; standard three-way fixed effects are tract of work-by-year, tract of residence-by-year, and tract pair. Outcome is log commuting flow. Treatment variables are mutually exclusive. Standard errors clustered by tract pair, tract of residence, and tract of work in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H5: Interactions of residential and workplace station proximity

	(1)			(2)		
	D contains station	D<250m from station	D<500m from station	D contains station	D<250m from station	D<500m from station
O contains station	0.094**	0.146*	-0.144*	0.108*	0.171*	-0.197**
	(0.038)	(0.077)	(0.076)	(0.063)	(0.100)	(0.094)
O<250m from station	0.021	0.017	0.043	0.096	0.118	0.051
	(0.059)	(0.074)	(0.103)	(0.075)	(0.110)	(0.111)
O<500m from station	0.009	-0.012	0.034	0.087	0.083	0.056
	(0.049)	(0.060)	(0.047)	(0.063)	(0.084)	(0.069)
N		291110			19222	
Control Group		All			Immediate '25 Plan	
Standard Three-Way FEs		Y			Y	
Subcounty Pair-×-Year FEs		Y			Y	
Highway Control		Y			Y	

High-dimensional fixed effects estimates of λ^D with log-linear estimator; standard three-way fixed effects are tract of work-by-year, tract of residence-by-year, and tract pair. Outcome is log commuting flow. Treatment variables. Standard errors clustered by tract pair, tract of residence, and tract of work in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H6: Bartik tests from Goldsmith-Pinkham, Sorkin, and Swift (2020), no subcounty fixed effects

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.245	-0.035	0.164
Positive	1.245	0.113	0.836

Panel B: Correlations of Industry Aggregates

	α_k	g_k	β_k	F_k	Var(z_k)
α_k	1				
g_k	0.043	1			
β_k	0.132	0.463	1		
F_k	0.148	-0.178	-0.477	1	
Var(z_k)	0.490	-0.112	-0.047	-0.025	1

Panel C: Top 5 Rotemberg weight industries

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	95 % CI	Ind Share
Manufacturing (durable)	0.395	-0.058	3.526	N/A	13.135
Transportation	0.226	-0.110	0.558	(-1.6,2.0)	4.141
FIRE	0.193	0.106	2.248	(-0.4,12.4)	7.805
Personal Services	0.124	0.178	5.181	(2.4,22.6)	3.565
Wholesale Trade	0.112	-0.058	-0.897	(-2.5,0.2)	4.919

Panel D: Estimates of β_k for positive and negative weights

	α-weighted sum	Share of overall β	Mean
Negative	-0.315	-0.126	1.730
Positive	2.827	1.126	1.985

Panel E: Alternative estimates and overidentification

	Bartik	TSLS	LIML	MBTSLS	HFUL
$\Delta \ln(W_{jt})$	2.512	1.457	2.911	1.571	2.470
	(1.094)	(0.662)	(1.835)	(0.705)	(5.065)
Over ID Test Stat.		34.2	22.2		23.9
p-value		[0.01]	[0.14]		[0.09]

This table reports statistics about Rotemberg weights and alternate IV estimators as suggested in Goldsmith-Pinkham, Sorkin, and Swift (2020). The results correspond to Table 4 column 5. In all cases, statistics reflect normalized growth rates. Panel A reports the share and sum of negative Rotemberg weights. Panel B reports correlations between the weights (α_k), the national component of growth (g_k), the just-identified coefficient estimates (β_k), the first-stage F-statistic of the industry share (F_k), and the variation in the industry shares across locations (VAR(z_k)). Panel C reports variation in the weights across years. Panel D reports the top five industries according to the Rotemberg weights. The 95% CI uses the weak-instrument robust CI from Chernozhukov and Hansen (2008) over a range from ?25 to 25 and is N/A if it exceeds that range, and Ind Share is the industry share (multiplied by 100). Panel E reports a variety of alternative estimates. TSLS uses each industry share separately as instruments. LIML reports estimates using the limited information maximum likelihood estimator with the same set of instruments. MBTSLS uses Anatolyev (2013) and Kolesár et al. (2015) with the same set of instruments. HFUL uses the HFUL estimator (Hausman et al. 2012) with the same set of instruments, and the J-statistic from Chao et al. (2014). p-values are in brackets.

Table H7: Bartik tests from Goldsmith-Pinkham, Sorkin, and Swift (2020), with subcounty fixed effects

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.290	-0.048	0.184
Positive	1.290	0.108	0.816

Panel B: Correlations of Industry Aggregates

	α_k	g_k	β_k	F_k	Var(z_k)
α_k	1				
g_k	-0.051	1			
β_k	-0.009	0.460	1		
F_k	0.180	-0.347	-0.468	1	
Var(z_k)	0.524	-0.112	-0.218	0.092	1

Panel C: Top 5 Rotemberg weight industries

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	95 % CI	Ind Share
Manufacturing (durable)	0.457	-0.058	2.980	N/A	13.149
Transportation	0.262	-0.110	-0.305	(-1.80,0.80)	4.143
FIRE	0.144	0.106	3.398	N/A	7.814
Health	0.137	0.050	-1.110	(-6.80,1.40)	7.047
Wholesale Trade	0.100	-0.058	-2.690	(-7.80,-1.10)	4.924

Panel D: Estimates of β_k for positive and negative weights

	α-weighted sum	Share of overall β	Mean
Negative	-0.178	-0.082	0.735
Positive	2.358	1.082	3.066

Panel E: Alternative estimates and overidentification

	Bartik	TSLS	LIML	MBTSLS	HFUL
$\Delta \ln(W_{jt})$	2.180	0.450	25.760	0.464	.
	(1.171)	(0.542)	(1363.467)	(0.813)	()
Over ID Test Stat.		75.9	0.8		.
p-value		[0.00]	[1.00]		[.]

This table reports statistics about Rotemberg weights and alternate IV estimators as suggested in Goldsmith-Pinkham, Sorkin, and Swift (2020). The results correspond to Table 4 column 6. In all cases, statistics reflect normalized growth rates. Panel A reports the share and sum of negative Rotemberg weights. Panel B reports correlations between the weights (α_k), the national component of growth (g_k), the just-identified coefficient estimates (β_k), the first-stage F-statistic of the industry share (F_k), and the variation in the industry shares across locations (VAR(z_k)). Panel C reports variation in the weights across years. Panel D reports the top five industries according to the Rotemberg weights. The 95% CI uses the weak-instrument robust CI from Chernozhukov and Hansen (2008) over a range from ?25 to 25 and is N/A if it exceeds that range, and Ind Share is the industry share (multiplied by 100). Panel E reports a variety of alternative estimates. TSLS uses each industry share separately as instruments. LIML reports estimates using the limited information maximum likelihood estimator with the same set of instruments. MBTSLS uses Anatolyev (2013) and Kolesár et al. (2015) with the same set of instruments. HFUL uses the HFUL estimator (Hausman et al. 2012) with the same set of instruments, and the J-statistic from Chao et al. (2014). p-values are in brackets.

Table H8: Transit and non-commuting fundamentals with half spatial decay

	$\bar{d}$ = 500m				$\bar{d}$ = 1km			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Effect on productivity								
I.) λ^A estimated using $\Delta\hat{\mathcal{A}} = \Delta\hat{A} - \mu\Delta\ln(\Upsilon^{Far})$								
Proximity$_i \times t$	0.031	0.030	0.017	0.021	0.040	0.041	0.027	0.035
	(0.039)	(0.039)	(0.038)	(0.043)	(0.037)	(0.038)	(0.037)	(0.043)
N	2469	1167	934	394	2469	1167	934	394
Effect on residential amenity level								
IV.) λ^B estimated using $\Delta\hat{\mathcal{B}} = \Delta\hat{B} - \eta\Delta\ln(\Omega^{Far})$								
Proximity$_i \times t$	0.050	0.068**	0.045	0.007	0.035	0.056*	0.025	-0.028
	(0.032)	(0.033)	(0.033)	(0.035)	(0.029)	(0.031)	(0.030)	(0.034)
N	2149	994	815	343	2149	994	815	343
Control Group	All	PER	Full '25 Plan	Immed. '25 Plan	All	PER	Full '25 Plan	Immed. '25 Plan

Results from sixteen regressions of transit proximity on local productivity after removing agglomeration. Here, the distance effect of agglomeration decays at half the values in Ahlfeldt et al. (2015). All regressions include tract fixed effects, subcounty-by-year fixed effects, and controls. Controls include changes in highway proximity and 1990 levels of log household income, share of residents with at least a high school degree, and manufacturing employment. Sample size reflects number of differenced tracts. Standard errors clustered by tract in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H9: Transit and non-mutable fundamentals

	$\Delta\hat{\mathbf{Y}}_{it}$							
	$\bar{d}$ = 500m				$\bar{d}$ = 1km			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Effect on inverse housing supply efficiency $\Delta\hat{C}$, λ^C								
Proximity$_i \times t$	0.006	0.007	-0.024	-0.041	0.007	0.012	-0.031	-0.053
	(0.049)	(0.051)	(0.051)	(0.058)	(0.044)	(0.047)	(0.048)	(0.057)
N	2172	996	818	348	2172	996	818	348
B. Effect on workplace amenity $\Delta\hat{E}$, λ^E								
Proximity$_i \times t$	-0.016	-0.083	-0.064	-0.115	-0.004	-0.087	-0.062	-0.138*
	(0.070)	(0.072)	(0.075)	(0.084)	(0.066)	(0.069)	(0.072)	(0.084)
N	2516	1168	935	395	2516	1168	935	395
Control Group	All	PER	Full '25 Plan	Immed. '25 Plan	All	PER	Full '25 Plan	Immed. '25 Plan

Results from sixteen regressions of transit proximity on local fundamentals. All regressions include tract fixed effects, subcounty-by-year fixed effects, and controls. Controls include changes in highway proximity and 1990 levels of log household income, share of residents with at least a high school degree, and manufacturing employment. Sample size reflects number of differenced tracts. Standard errors clustered by tract in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H10: Transit, income change, and land use change (robustness)

	$\Delta\hat{\mathbf{Y}}_{it}$							
	$\bar{d}$ = 500m				$\bar{d}$ = 1km			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Change in residential land								
Proximity$_i \times t$	0.006***	0.002	0.001	0.001	0.007***	0.003	0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
N	2468	1152	920	385	2468	1152	920	385
B. Change in household income								
Proximity$_i \times t$	-0.016	-0.006	-0.006	-0.019	-0.025	-0.014	-0.015	-0.034*
	(0.017)	(0.017)	(0.017)	(0.018)	(0.016)	(0.017)	(0.017)	(0.019)
N	2476	1142	915	380	2476	1142	915	380
Control Group	All	PER	Full '25 Plan	Immed. '25 Plan	All	PER	Full '25 Plan	Immed. '25 Plan

Results from sixteen regressions of transit proximity on residential land use and household income. All regressions include tract fixed effects, subcounty-by-year fixed effects, and controls. Controls include changes in highway proximity and 1990 levels of log household income, share of residents with at least a high school degree, and manufacturing employment. Sample size reflects number of differenced tracts. Standard errors clustered by tract in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H11: Effect of LA Metro Rail on Residential Commute Share using Rail Transit

	Residential Commute Share using Rail Transit							
	$\bar{d}$ = 500m				$\bar{d}$ = 1km			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proximity$_i \times t$	0.0084***	0.0081***	0.0081***	0.0079***	0.0078***	0.0077***	0.0077***	0.0076***
	(0.0015)	(0.0014)	(0.0014)	(0.0015)	(0.0012)	(0.0012)	(0.0013)	(0.001)
N	2262	1037	848	371	2262	1037	848	371
Control Group	All	PER	Full '25 Plan	Immed. '25 Plan	All	PER	Full '25 Plan	Immed. '25 Plan

Results from eight regressions of transit proximity on subway/light rail commute share. All regressions include tract fixed effects, subcounty-by-year fixed effects, and controls. Samples: 'All' is the Full Sample, 'Sim' is Subway Plan (Immediate), 'Sal' is Subway Plan (All), and PER is the PER Sample. Controls include changes in highway proximity and 1990 levels of log household income, share of residents with at least a high school degree, and manufacturing employment. Sample size reflects number of differenced tracts. Standard errors clustered by tract in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table H12: Welfare effects of model extensions (% change in welfare)

	Partial Equilibrium (1)	General Equilibrium (2)	General Equilibrium + Spillovers (3)
Baseline: Commuting Effect through 2000	0.04410	0.04404	0.04324
+ Dynamic Effect (through 2015)	0.08032	0.07965	0.07838
+ Congestion Effect	0.10671	0.10632	0.10431
+ Dynamic & Congestion Effects	0.14295	0.14196	0.13946
Baseline & Reduced Land Use Regulation	0.12234	0.10574	0.10371
+ Dynamic Effect (through 2015)	0.15859	0.14266	0.14040
+ Congestion Effect	0.18500	0.16806	0.16481
+ Dynamic & Congestion Effects	0.22127	0.20500	0.20153
Baseline & 5% Amenity	0.10757	0.10688	0.10478
+ Dynamic Effect (through 2015)	0.14544	0.14355	0.14118
+ Congestion Effect	0.17022	0.16920	0.16588
+ Dynamic & Congestion Effects	0.20811	0.20589	0.20230
Baseline & 4% Productivity	0.36608	0.28847	0.28735
+ Dynamic Effect (through 2015)	0.40241	0.32548	0.32400
+ Congestion Effect	0.42888	0.35090	0.34857
+ Dynamic & Congestion Effects	0.46524	0.38794	0.38524

This table gives the percentage change in welfare for various model scenarios (e.g., 0.04409 is a 0.044% change in welfare). Columns 1–3 show partial equilibrium results, general equilibrium results the ignore endogenous agglomeration, and general equilibrium results that account for endogenous agglomeration. Partial equilibrium reflects only changes in items that feed into the utility function, but no feedbacks (but effects to A and C do have price effects). The first panel includes the results in the main paper, whereas the other panels present experiments presuming other effects become present: Reduced Land Use Regulation assumes $\lambda^C = -0.3297$ just in tracts containing transit stations, such that residential density increases in those locations by 10%; 5% Amenity assumes $\lambda^B = 0.05$ with the 500m proximity measure of treatment; and 4% Productivity assumes $\lambda^A = 0.04$ with the 500m proximity measure of treatment.