The Costs of Access: Freeway Disamenities Across US Cities

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Abstract

We construct city-level measures of freeway disamenities and examine their association with metropolitan growth. We combine neighborhood-level estimates from Brinkman and Lin (2024) with calibrated spatial models for U.S. metropolitan areas. Each city measure is based on a counterfactual that removes estimated disamenities while holding modeled travel times fixed. Cities with larger estimated disamenities grew more slowly, conditioned on total freeway mileage and initial population. Total freeway mileage is positively associated with growth in the same specification. Estimated disamenities are larger in cities with greater 1950 populations, more centralized freeway networks, and coastal geography. These patterns are consistent with local quality-of-life costs attenuating regional access-related growth benefits.

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1 Introduction

Highways reduce travel times and connect workers to jobs, but they impose noise, pollution, and physical barriers on nearby neighborhoods. Boston's Big Dig illustrates this central tradeoff in urban highway policy. The project replaced roughly 1.5 miles of the elevated Central Artery with a downtown tunnel; the broader project created approximately 3.5 miles of underground highway at a total cost of roughly $15 billion. The project's extraordinary expense — making it one of the costliest infrastructure undertakings in U.S. history — shows that local freeway costs can be quantitatively important even when highway access remains valuable. But it also raises a critical question: What determines the magnitude of freeway disamenities? And why do they vary so dramatically across cities that some warrant multi-billion dollar mitigation efforts while others apparently do not?

The variation in disamenity costs may reflect different local tradeoffs across metropolitan areas. Highways expanded access within and across cities while cutting through established neighborhoods. Their local costs likely depended on where new routes passed relative to established population and employment, subject to geographic constraints. Cross-city variation may therefore reflect both highway-network configuration and the urban structure surrounding that network. Where freeways delivered the largest access gains may also be where their disamenity costs were hardest to avoid.

Prior research largely measures highway benefits and costs separately, making it challenging to evaluate their balance across different metropolitan areas. Highways reduce commuting and trade costs, reshape metropolitan development, and are associated with city growth (Baum-Snow 2007, 2020; Duranton and Turner 2012; Redding and Turner 2015). Highway proximity also reduces local quality of life through pollution, traffic danger, noise, barrier effects, crime, and neighborhood change (Anderson 2020; Brinkman and Lin 2020, 2022, 2024; Currie and Walker 2011). But these literatures are largely disconnected, and it is unclear how these neighborhood-level costs aggregate across cities and why their measured magnitude varies.

To help bridge this gap, we measure city-level freeway disamenities and examine their cross-city variation. We combine neighborhood-level estimates from Brinkman and Lin (2024) with calibrated quantitative spatial models (Ahlfeldt et al. 2015) for U.S. metropolitan areas. We construct each city measure using a counterfactual that removes estimated freeway disamenities while holding modeled travel times fixed. The counterfactual changes recovered neighborhood amenities and allows residential and employment locations, wages, rents, and commuting to adjust within each city. We measure the resulting change in expected utility. Across cities, the mean estimated disamenity is a 3.8 percent utility loss, with a standard deviation of 1.5 percent, indicating substantial dispersion in freeway disamenities across U.S. cities.

We then examine two relationships: the association between estimated disamenities and long-run metropolitan growth, and the city characteristics associated with larger estimated disamenities. We regress long-run metropolitan population growth on estimated disamenities, total freeway mileage, and initial population. Total freeway mileage proxies for highway infrastructure (but we acknowledge that it may not fully measure access benefits). A separate cross-city analysis relates estimated disamenities to baseline city size, contemporary urban structure, network configuration, and geography.

Estimated freeway disamenities are negatively associated with long-run metropolitan growth. A one-percentage-point difference in estimated utility loss is associated with 8.5 percent slower population growth over 1950–2019, conditioned on total freeway mileage and initial population. Total freeway mileage is positively associated with growth in the same specification. These patterns are consistent with local quality-of-life costs attenuating access-related growth benefits. Estimated disamenities are also larger in cities with greater 1950 populations, more centralized freeway networks, and coastal geography. We observe substantial regional variation, with larger measured disamenities in Midwest and Northeast cities, consistent with reduced flexibility in routing highways away from populated areas in older, denser cities.

Thus, we connect research on the local quality-of-life costs of freeways with research on their regional growth benefits in three steps. One, we translate neighborhood-level disamenity estimates into comparable city-level measures. Two, we document how those measures vary with urban structure, network configuration, and geography. Three, we examine their association with long-run metropolitan growth alongside total freeway mileage.

Section 2 reviews evidence on highway access, local costs, and aggregation. Section 3 presents the conceptual framework. Section 4 constructs and interprets the city-level disamenity measures. Section 5 examines their association with metropolitan growth. Section 6 documents their cross-city correlates. Section 7 concludes.

2 Highways, cities, and neighborhoods: A selective literature review

2.1 Highway access and aggregate urban change

Highways reduce commuting costs and are associated with aggregate urban and regional growth. Comprehensive reviews by Redding and Turner (2015) and Donaldson (2025) document that transportation infrastructure generates aggregate benefits through reduced trade and commuting costs, expanded market access, and productivity improvements. Duranton and Turner (2012) estimate that a 10 percent increase in highway lane miles is associated with 1.5 percent higher employment growth over 20 years in U.S. cities, using planned and historical routes as instruments.

Highways also reshape the spatial distribution of population and employment within metropolitan areas. Baum-Snow (2007) estimates that Interstates reduced central city populations by 18 percent relative to the counterfactual, using planned routes as an instrument for actual construction. Baum-Snow (2020) shows that the Interstate system contributed substantially to the decentralization of employment as well as residents, generating suburban growth alongside central-city population decline.

Beyond commuting access, roads affect intercity trade and economic specialization. Michaels (2008) finds that U.S. highway access raised manufacturing employment and earnings, particularly in rural counties. Chandra and Thompson (2000) show that highway construction raised earnings in directly affected nonmetropolitan counties. Duranton, Morrow, and Turner (2014) show that road access shapes the volume and composition of trade between U.S. cities. Velasquez-Cabrera (2024) separates commuting-access and market-access channels and quantifies their contributions to suburban growth and urban-core decline.

This literature establishes that highways generate quantitatively important access benefits. It generally abstracts from local quality-of-life losses associated with freeway proximity and does not aggregate disamenity costs into city-level welfare measures.

2.2 Local disamenities, barriers, and distributional effects

Highway proximity imposes local costs through multiple channels. The most extensively studied is traffic-related air pollution. Currie and Walker (2011) find that traffic congestion significantly worsens infant health outcomes near tollbooths. Anderson (2020) documents substantial mortality effects from long-term exposure to traffic-related particulate matter. Valenzuela-Casasempere (2026) uses variation from Interstate Highway construction to estimate long-run mortality consequences of highway proximity. Epidemiological work by Gauderman et al. (2007) and Hoek et al. (2002) establishes biological pathways from traffic pollution to respiratory and cardiovascular disease.

Highways impose additional costs through physical severance, traffic danger, and crime. Appleyard's (1981) foundational work shows that higher traffic volumes reduce social interaction among residents of the same street. Aiello et al. (2024) document that urban highways reduce social ties between the neighborhoods they divide. Anciaes and Mindell (2021) review community severance as a distinct disamenity category. Wang (2025) shows that freeways reduce neighborhood social connectivity through barrier effects. Brinkman and Lin (2024) show increases in travel times and reduced travel volumes between neighborhoods severed by freeways. Nehiba and Tyndall (2023) analyze traffic externalities, and Calamunci and Lonsky (2025) find that highway proximity is associated with higher crime.

Evidence from housing prices and population choices reveals how residents value these costs. Downs (1970) identified "uncompensated non-construction costs" — noise, air pollution, visual disamenity, and community disruption — imposed on households near urban highways. Nelson (1982) documents negative price gradients near highways using hedonic methods. Álvez (2025) provides more recent evidence on disamenity capitalization. Moretti and Wheeler (2025) use quasi-experimental variation from noise barrier construction to estimate households' willingness to pay for reduced traffic noise, recovering an aggregate economic cost of $110 billion nationwide. Brinkman and Lin (2024) provide an omnibus revealed-preference estimate: rather than isolating individual disamenity channels, they recover the total quality-of-life loss from freeway proximity as reflected in population, housing prices, and incomes — encompassing noise, pollution, severance, and all other sources simultaneously. Two complementary identification strategies — dynamic within-city variation comparing central to peripheral neighborhoods over time, and cross-sectional variation within Chicago conditioning on job access — yield a central estimate of an 18 percent decline in neighborhood amenities, attenuating by 95 percent at 2.4 miles. These costs fell most heavily in central urban neighborhoods, and their concentration foreshadows the displacement and distributional consequences that the evidence below documents.

Highway construction through established urban neighborhoods has been associated with displacement, racial segregation, and concentrated decline. Roberto and Hwang (2017) study how physical barriers — including highways, railroad tracks, and dead ends — structure residential segregation. Bagagli (2025), Mahajan (2024), and Weiwu (2025) each document segregation impacts of highways using different data and identification strategies. Ananat (2011) and Chyn, Haggag, and Stuart (2026) use the arrangement of nineteenth-century railroad tracks as instruments for metropolitan segregation, finding that higher segregation reduces upward mobility for Black children and widens racial income disparities. DiMento and Ellis (2013) and Mohl (2002, 2004, 2008) provide historical accounts of the politics and distributional consequences of urban Interstate construction.

Freeway removal and conversion provide complementary evidence on the value of mitigation. Cervero, Kang, and Shively (2009) document that housing prices near San Francisco freeways rose after removal or conversion. Cheng (2025) documents localized increases in population, property values, and demographic change following removal of Rochester's Inner Loop. These findings are consistent with the presence of disamenities, but removal effects should not be assumed symmetric with construction effects: local context, equilibrium responses, and accompanying public investment may differ across settings.

2.3 From neighborhood effects to city-level outcomes

Local disamenity estimates do not translate mechanically into city-level welfare losses. Spatial equilibrium models predict that residents and firms adjust their location choices, wages, and rents in response to any local shock. Summing neighborhood-level losses would overstate aggregate welfare effects to the extent that residents sort away from disamenities, rents compress, or commuting patterns adjust.

Quantitative spatial models aggregate local shocks while capturing adjustment in wages, rents, and location choices. Ahlfeldt et al. (2015) develop a multi-location model with heterogeneous location fundamentals and commuting costs that supports counterfactual analysis of local amenity changes. Monte, Redding, and Rossi-Hansberg (2018) show that accounting for internal migration substantially changes welfare estimates of regional shocks. Redding and Rossi-Hansberg (2017) review this class of models and their applications to trade and urban economics. In each framework, aggregate welfare depends on how rents, wages, commuting, and employment all adjust to a local shock — not only on the direct quality-of-life change at affected locations.

Spatial equilibrium frameworks from urban economics provide complementary foundations. Roback (1982) shows that amenities are reflected in wages and rents in equilibrium: a city with worse amenities must compensate residents through lower rents or higher wages. Albouy and Lue (2015) apply this framework to estimate quality-of-life levels across U.S. cities. These frameworks clarify why local hedonic evidence does not directly measure aggregate city welfare.

We use the framework of Ahlfeldt et al. (2015) to translate neighborhood-level estimates from Brinkman and Lin (2024) into comparable city-level disamenity measures. The counterfactual removes estimated disamenities while holding modeled travel times fixed — conceptually similar to mitigating freeway disamenities without removing highway access, as in Boston's Big Dig or current proposals for capping and burial. Section 3 presents the conceptual framework.

3 Disamenities versus transportation benefits

Our analysis is based on a quantitative spatial model similar to Ahlfeldt et al. (2015), which we use to translate neighborhood-level freeway disamenities into city-level welfare measures. The full model is described in Appendix A. In the framework, each location has a fixed amount of land and is characterized by a productivity and a residential consumption amenity. Workers choose where to live and work subject to commuting costs, firms choose locations based on productivity and labor costs, and equilibrium is determined by the spatial distribution of wages, rents, employment, population, and commuting flows. Generally, this class of models is useful in analyzing equilibrium effects of changes to location fundamentals, transportation costs, or local policy interventions.

To develop intuition, we consider a simplified version of the framework. Under the assumptions of a monocentric city, no idiosyncratic location preferences, and a linear geography, the quantitative spatial model reduces to the framework developed below.[1] The simplified

[1] For simplicity, we use a linear-city framework. The same qualitative relationship between transportation access, amenities, and population holds in a standard circular city, but the resulting expressions are less tractable.

model preserves the key tradeoff between transportation access and freeway disamenities while yielding tractable expressions for population and growth. The city-level disamenity measures used throughout the paper are constructed using the full model, while the simplified framework developed below is used to illustrate the key mechanisms underlying the tradeoff between transportation access benefits and freeway disamenities.

Consider a linear city denoted i where all employment is located at the center $x = 0$, and workers live some positive distance from the center x. Workers are paid a fixed wage w_0, and there is an iceberg cost of commuting such that the net wage at any location in the city is $w(x) = w_0 e^{-\kappa\tau_i x}$, where κ is the time cost of commuting parameter. The parameter τ_i is the time needed to travel a distance x and varies by city based on freeway infrastructure. Note here that we assume that the wage is exogenous. In equilibrium, it is likely that wages increase with lower travel times due to increases in productivity from agglomeration or reductions in intercity trade costs.[2] In addition, workers pay land rent $r(x)$ to an absentee landlord.

Workers have increasing utility over land l and a numeraire consumption good c with price normalized to 1. In addition, workers gain utility from the amenity associated with a city, denoted B_i. This captures all consumption amenities in a city and importantly depends on the amount and configuration of freeway infrastructure. Workers choose land and consumption to maximize a utility given by the following function that is assumed log linear with a constant share of consumption denoted β.

$$U = B_i c^{\beta} l^{1-\beta}$$

The city exists in a larger economy and therefore workers must receive an equal reservation utility everywhere in the city, which is normalized to 1. The budget constraint is given by $w(x) = r(x)l + c$. Solving the maximization problem and omitting constants, the indirect utility function is given by,

$$V(x) = B_i \, w_0 e^{-\kappa\tau_i x} r(x)^{\beta-1},$$

[2] Freeway disamenities may also affect productivity indirectly by dispersing workers and firms, potentially reducing labor-market thickness and knowledge spillovers. These channels are not explicitly modeled here.

and the population density $n_i(x)$ for a given distance from the city center is given by,

$$n_i(x) = B_i^{\frac{1}{1-\beta}} w_0^{\frac{\beta}{1-\beta}} e^{-\kappa\tau_i \frac{\beta}{1-\beta} x}$$

By integrating the density function over the entire city from 0 to ∞ and taking logs, we get the following simple expression for total population N_i in the city.[3]

$$\ln N_i = \frac{1}{1-\beta} \ln B_i + \frac{\beta}{1-\beta} \ln w_0 - \ln\left(\kappa\tau_i \frac{\beta}{1-\beta}\right) \tag{1}$$

Adding freeways to a city has two important effects. The first is that travel times are reduced through a decrease in τ_i. This reduces commuting costs and increases access to land farther from the city center, increasing population. Although not explicitly modeled here, wages may increase in equilibrium through increased intercity trade or increases in agglomeration benefits from lower transportation costs within the city, also increasing population. The second *offsetting* effect is that there are decreased amenity values for neighborhoods from noise, pollution, or barrier effects, where freeways cut off access to nearby neighborhoods. This effect is captured in a reduction in B_i. When amenities are reduced, workers must be compensated through lower rents and lower population density, which results in lower total population. The model predicts that lower transportation costs increase population while lower amenities reduce population. We use this prediction to examine freeway mileage and estimated disamenities jointly in the cross-city growth analysis.

Total freeway mileage proxies for highway infrastructure, though we acknowledge that it does not measure every change in transportation costs, network access, or congestion. This is similar to the analysis of Duranton and Turner (2012) who find a positive relationship between changes in freeway miles and changes in population. As a proxy for freeway disamenities, we turn to a structural model-based approach to calculate a measure of freeway disamenities in each city. The calculation of these city-level disamenity measures is described in Section 4.

[3]For tractability, we do not impose an explicit urban fringe determined by agricultural land rents. Because equilibrium residential density declines exponentially with distance from the center, the population integral converges and total population remains finite even without a sharp urban boundary. Introducing a standard urban fringe would not alter the qualitative results.

4 Measuring city-level disamenities

We now use the quantitative spatial model to construct a city-level measure of freeway disamenities. The measure is derived from a counterfactual experiment that removes freeway disamenities while holding transportation benefits fixed. This section describes the calibration of the model, the construction of the disamenity measure, and its interpretation.

We calibrate the model by taking general parameters from the literature and using data on worker population and employment at the census tract level and travel times to recover location-specific amenity and productivity for all cities. Population and employment data come from the 2019 Longitudinal Employment and Household Dynamics Origin-Destination Employment Statistics (LODES) from the U.S. Census. These data provide information on worker residential population, employment, and land area for each census tract. Data on travel times are provided by the Urban Institute, who calculated travel times for over 154 million Census tract pairs. Lastly, the location of major highways comes from the Census Tiger Line data on primary roads in 2010.

We construct a measure of total freeway disamenities for each city in our sample using the structural model by performing a counterfactual simulation where the disamenities from freeways are completely mitigated, but travel times remain the same. This represents an intervention such as burying freeways below ground to remove negative effects on neighborhoods while maintaining transportation benefits. For this paper, this allows us to compare total disamenities across cities. We use estimates of freeway disamenities from Brinkman and Lin (2024).[4] In that paper, it is estimated that freeways lead to an 18 percent decline in neighborhood amenities with the effects attenuating 95 percent at 2.4 miles from the freeway.

In the counterfactual simulation, we adjust the location amenities by removing freeway disamenities and then resolve the equilibrium and calculate a new expected utility for res-

[4]The freeway disamenity parameters were estimated in that paper for Chicago using data from the Census Transportation Planning Package (2000). These parameters are then applied within the quantitative spatial model to construct city-specific disamenity measures for each metropolitan area in our sample. Appendix Figure 4 illustrates the analogous disamenity surface for Chicago based on the 2019 LODES data.

idents. The difference in outcomes between the counterfactual simulation and the baseline calibration provides a measure of freeway disamenities for each city by calculating the change in expected utility with total disamenity mitigation.

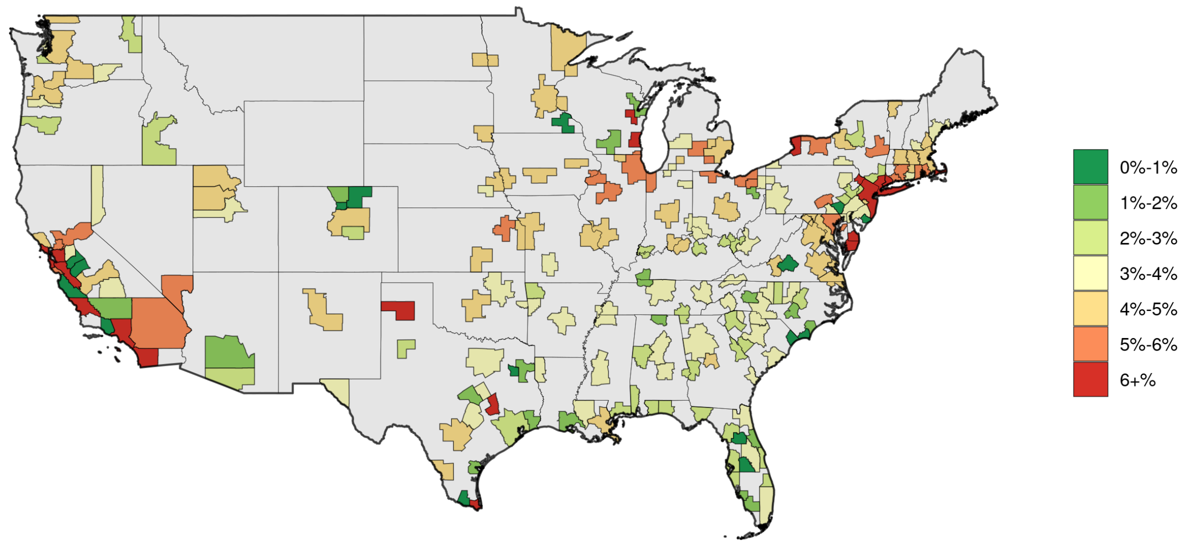
4.1 Measurement and interpretation

The city-level disamenity measures support relative cross-city comparisons more directly than absolute welfare claims. Figure 1 shows the measures for all metropolitan areas in the sample; the mean estimated utility gain from complete disamenity mitigation is 3.8 percent, with a standard deviation of 1.5 percent. (Appendix B reports estimates by city.) Mechanically, the measure will be larger in cities where freeway exposure intersects denser contemporary residential locations, because higher residential density near a freeway amplifies the measured aggregate quality-of-life loss. If neighborhood amenities were fixed and exogenous to highway construction, these figures would represent expected percentage welfare gains for each city's residents, which is the literal reading of the model's output. In practice, absolute magnitudes depend on calibrated parameters; the cross-city ranking is more robust to alternative calibration choices.

Contemporary urban structure enters the measure directly, which raises endogeneity concerns. We calibrate the model using contemporary population, employment, and commuting data, then recover location-specific amenities and productivities that rationalize the observed spatial distribution. These recovered fundamentals reflect equilibrium sorting by households and firms over several decades, including responses to highway construction. To the extent that contemporary location fundamentals contain endogenous responses to highways, through either household sorting or the political economy of routing decisions, the estimated measures blend the true disamenity with these equilibrium adjustments.

Our approach provides some discipline on these concerns. Common parameters from Brinkman and Lin (2024) ensure that cross-city variation reflects differences in city and network characteristics rather than differences in estimated parameters: we impose a common

Figure 1: Measure of Freeway Disamenities by U.S. Metropolitan Areas

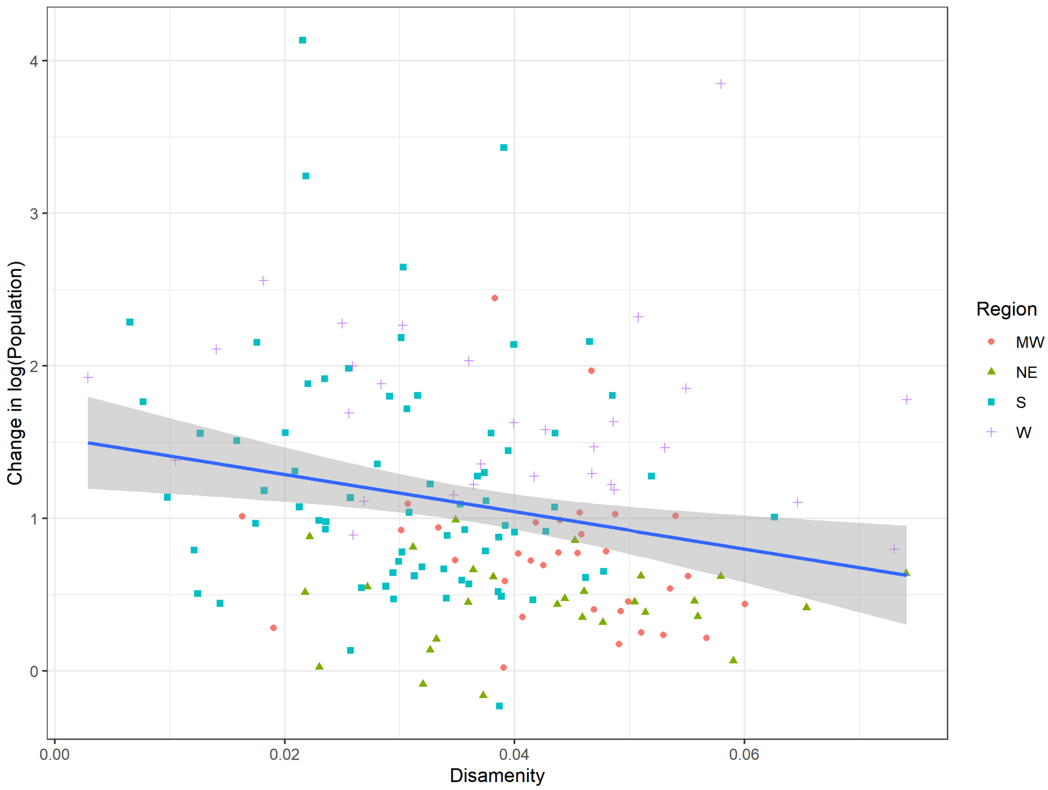


This figure shows the calculated measure of freeway disamenities for all metropolitan areas in our sample. The values represent potential percentage welfare loss from negative quality-of-life effects holding modeled travel times fixed.

disamenity gradient and attenuation profile across cities. Conditioning on initial population and examining long differences over the highway construction period further limits the role of pre-existing differences. Endogeneity concerns from highway placement and the contemporary spatial equilibrium apply to any measure of this type, but they bear on absolute magnitudes more directly than on the cross-city ranking, which is the principal empirical object of the analysis.

The model does not capture every channel through which highways affect cities. The counterfactual removes estimated freeway disamenities while holding modeled travel times fixed. This separates the amenity channel from the travel-time channel in the model, attributing the measured welfare change to quality-of-life rather than to commuting costs. However, it does not hold every access benefit constant. Freeway networks affect congestion, market access, and agglomeration productivity through channels that the counterfactual does not capture, because these operate at spatial scales or through mechanisms outside the model.

Figure 2: Population change is negatively correlated with disamenities



This figure shows the change in the natural log of population between 1950 and 2019 for metropolitan areas plotted against our disamenity measure.

We use these measures in two cross-city analyses. Section 5 examines their association with long-run population growth, conditioned on total freeway mileage and initial population. Section 6 relates them to baseline city size, contemporary urban structure, freeway-network configuration, and geography.

5 Freeways, disamenities, and population growth

Estimated freeway disamenities are negatively associated with metropolitan growth. Figure 2 shows this unconditional relationship.

We next estimate the relationship conditioned on total freeway mileage and initial population, following Duranton and Turner (2012). Equation (1) predicts that highways affect population through two offsetting channels: transportation improvements that increase access and freeway disamenities that reduce neighborhood quality of life. The disamenity measure constructed in Section 4 provides a city-level index of the latter channel, while total freeway mileage serves as a proxy for the former. The resulting specification can be viewed as a reduced-form representation of the population response to these two channels following highway construction:

$$\Delta \ln N_i = \alpha_0 + \alpha_1 Disamenity_i + \alpha_2 \ln FreewayMiles_i + \alpha_3 \ln 1950pop_i + \epsilon_i \tag{2}$$

The dependent variable $\Delta \ln N_i$ is the change in the natural log of metropolitan area population between 1950 and 2019[5], $Disamenity_i$ is our measure of contemporary freeway disamenities derived from the structural model, and $FreewayMiles_i$ is the total freeway miles in each metropolitan area.

Total freeway mileage is a natural summary of highway network scale.[6] Duranton and Turner (2012) treat a related measure, total lane-miles, as the primary measure of the highway access channel, finding that a 10 percent increase raises employment growth by approximately 1.5 percent. We follow the same convention, pairing mileage as the access measure with our disamenity measure as the quality-of-life cost measure (with the maintained caveat that mileage does not fully capture travel-time savings, network connectivity, or market access, so the coefficient on mileage does not represent its causal effect). While most freeways were built after 1955 under the Interstate Highway program, total freeway miles are strongly correlated with city size, so we control for initial 1950 population. Conditional on total mileage, the disamenity measure proxies quality-of-life differences arising from how freeway construction was implemented across cities; we expect a negative coefficient on disamenities and a positive coefficient on mileage.

The results are shown in Table 1. The first three columns show ordinary least squares

[5] Population data for consistent 2020 definitions of metropolitan areas for 1940, 1950, and 2020 come from IPUMS-NHGIS (Manson et al. 2019).

[6] Highway data come from the Census Tiger Line data on primary roads in 2010.

estimates. The first column shows the correlation between the disamenity measure and population growth. Larger disamenities are strongly correlated with slower population growth after freeway construction. In column (2), results are shown using only the natural log of total freeway miles along with 1950 population as controls. This shows that, controlling for population, more freeways were associated with faster growth. In column (3), the variables are included in a single regression. In this specification, the coefficient on disamenities remains negative, while the coefficient on freeway miles is positive. Lastly in column (4), as a robustness check, we include the natural log of 1940 population, as well regional fixed effects. The results are consistent with disamenities attenuating access-related growth benefits of freeway construction.

While the quantitative estimates of disamenities are significantly affected by modeling assumptions, the coefficient roughly suggests that a one percent loss in utility from freeway disamenities was associated with 8.5 percent slower growth over the time period, after controlling for total freeway miles. For reference, the average city in the sample had an estimated 3.8 percent loss in expected utility due to disamenities, and a standard deviation of 1.5 percent. The interpretation of the coefficient on freeway miles is that a one percent difference in freeway miles is associated with roughly 0.5 percent higher population growth.

Our estimates are roughly consistent with the findings of Duranton and Turner (2012), though the two approaches measure somewhat different objects. Duranton and Turner estimate the net effect of highway infrastructure on urban growth, which reflects both transportation access benefits and any offsetting freeway disamenities. In contrast, our specification includes separate measures of freeway mileage and disamenities, allowing us to decompose these effects. The positive coefficient on freeway mileage captures the access-related component of growth, while the disamenity measure captures the offsetting quality-of-life costs associated with freeway construction. Duranton and Turner estimate that a 10 percent increase in lane miles leads to a 1.5 percent increase in employment over a 20-year period, or an elasticity of 0.15. Our OLS estimate of 0.4 exceeds this, which could be attributed to

Table 1: Population Change

	Dependent variable:					
	Change in natural log of population					
	OLS				*IV*	
	(1)	(2)	(3)	(4)	(5)	(6)
Disamenity	-12.194^{***}		-9.790^{**}	-12.970^{***}	-14.796^{***}	-45.568^{*}
	(4.154)		(3.877)	(3.391)	(4.554)	(23.896)
ln(Total Miles)		0.435^{***}	0.489^{***}	0.402^{***}	0.748^{***}	0.859^{***}
		(0.063)	(0.066)	(0.055)	(0.127)	(0.167)
ln(Pop 1950)		-0.585^{***}	-0.559^{***}	1.082^{***}	-0.682^{***}	-0.566^{***}
		(0.056)	(0.056)	(0.260)	(0.078)	(0.134)
ln(Pop 1940)				-1.503^{***}		
				(0.247)		
Regional Controls				Y		
Constant	1.532^{***}	5.959^{***}	5.690^{***}	4.092^{***}	5.954^{***}	5.003^{***}
	(0.164)	(0.540)	(0.542)	(0.470)	(0.578)	(1.019)
Weak IV (Disamenity)						4.238^{***}
Weak IV (Total Miles)					66.345^{***}	34.021^{***}
Cragg-Donald						3.38
Wu-Hausman					6.731^{**}	5.503^{***}
Observations	162	162	162	162	162	162
R^2	0.051	0.406	0.429	0.656	0.373	0.093
Adjusted R^2	0.045	0.398	0.418	0.640	0.361	0.076

This table shows the results of regressions of the change in the natural log of population between 1950 and 2019 on our disamenity measure and total freeway miles. Columns (1) through (4) use ordinary least squares, while column (5) instruments for freeway miles using planned miles, and column (6) also includes average tract proximity to a coastline as an instrument for the disamenity. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

the fact that we measure cumulative population growth over a longer time horizon (70 years versus 20 years) and use total freeway miles rather than changes in lane miles. Population may also respond more elastically than employment to highway infrastructure.

A confounding factor that has commonly been addressed in the literature is that the intensity of freeway construction may be correlated with unobserved growth factors in cities. The direction of bias is ambiguous given that freeways may have been targeted to cities that were expecting growth, or freeways may have purposely added to cities that were lagging.

Following the literature[7], we use the 1947 national highway plan as an instrument for total freeway miles in a city. The validity of this plan as an instrument is derived from the fact that it was roughly drawn to connect nearby cities and is thus likely uncorrelated with growth factors. Specifically, our instrument is the natural log of total planned miles in a metropolitan area from the 1947 plan. Column (5) shows the results using the highway plan to instrument for total freeway miles. In this case, the coefficients on both the disamenity and the freeway miles remain significant and increase in magnitude.

We may also may be concerned that our disamenity measure is correlated with unobserved growth factors. The ideal instrument in this case would be something that shifts the configuration of freeways and affects the disamenity but is uncorrelated with growth factors after controlling for observables. Here we use a the average distance of a census tract in a city to a coastline. The idea is that in cities that are situated near water, it is difficult to route freeways away from densely populated areas. Column (6) shows the results using both instruments. Again, the coefficients remain significant, and the magnitude of the disamenity coefficient increases substantially. However, the weak-instrument diagnostics suggest that these IV estimates should be interpreted with some caution. Further, the exclusion restriction may be not be satisfied: proximity to water may be correlated with housing supply constraints or changes in demand. Our IV estimates of 0.7 to 0.8 for total freeway miles are somewhat larger, potentially reflecting that the 1947 highway plan identifies cities where highways were particularly consequential for long-run growth, or that long-run elasticities exceed medium-run effects as population fully adjusts to infrastructure changes.

Calibrated disamenity measures rely on contemporary population distributions, which reflect equilibrium sorting responses to highways. If highways were systematically routed through neighborhoods with poor pre-existing fundamentals, our measures could partially capture those conditions rather than highway effects. Importing common parameters from Brinkman and Lin (2024) rather than estimating them separately for each city provides

[7]See Baum-Snow (2007) and Duranton and Turner (2012) for examples of similar instruments used in the literature.

some discipline: the cross-city ranking depends on city and network characteristics, not on city-specific parameter choices. Conditioning on initial population and examining long differences over the highway construction period further limits the role of pre-existing differences. Instrumental-variable estimates using planned routes and geographic features as instruments yield results consistent with the OLS patterns; we treat these as suggestive given uncertainty about the exclusion restrictions.

6 Cross-city correlates of freeway disamenities

Freeway disamenities should be larger where highway networks intersect dense residential locations. The degree of that intersection reflects the joint configuration of cities and their highway networks. To provide access benefits, freeways must reach employment centers, an objective that guided early Interstate highway planning (American Association of State Highway Officials 1957); but where high-amenity residential neighborhoods cluster near job centers, routing toward employment places the highway through established communities. Cities with dense residential settlement before Interstate construction faced this tradeoff most acutely: durable investment in established neighborhoods left little room to add highways without affecting community quality of life. Geographic constraints compound this: coastlines and difficult topography reduced flexibility to route freeways away from populated areas while still serving employment centers.

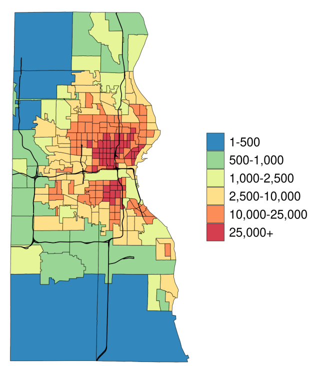
These mechanisms motivate four groups of city characteristics we examine as correlates of estimated disamenities. One, 1950 population measures baseline city size before most Interstate construction. Two, contemporary residential and employment centralization describe the urban structure surrounding the network. Three, total and central freeway mileage describe network intensity and configuration. Four, coastlines and slope describe geographic constraints. We interpret associations with these variables as consistent with the predicted mechanisms rather than as identified causal effects.

Figure 3 shows an example of the relationship between neighborhood change and freeway construction. The maps cover the area of existing census tracts in Milwaukee, Wisconsin in 1950. Panel (a) is a map of population density in 1950 and panel (b) is a map of the population density in 2019. The map in panel (c) shows the percentage amenity loss calculated from the calibrated model. In Milwaukee, freeways were built directly through the central business district, and passed through dense established neighborhoods. Populations in these neighborhoods declined substantially, particularly neighborhoods directly to the northwest of downtown, where a large share of the housing stock was abandoned and eventually removed. Milwaukee had one of the largest disamenity measures in our sample. Freeway construction was likely challenging given that Milwaukee was a large established city by 1950 and was somewhat geographically constrained due to the proximity of the central business district to Lake Michigan. Today, public officials and citizens seem aware of the negative effects of the freeways in the city center: the Wisconsin Department of Transportation is considering removing a mile-long stretch of I-794 through downtown, with hopes of spurring development in the area (Lathers 2026).

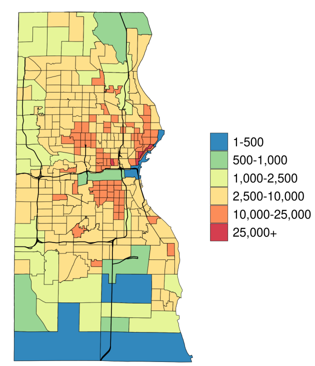
To explore the variation in freeway disamenities across metropolitan areas, we regress our disamenity measure on various characteristics of cities and their freeway networks. This exercise illustrates how features of cities are associated with larger quality of life losses associated with freeways. For this analysis, we collect additional data from several sources. The location of central business districts follows the definitions of Fee and Hartley (2013) who use data from the 1982 Census of Retail Trade. Data on rivers and coastlines come from the National Weather Service and the Census Tigerline respectively. Finally, the average slope of census tracts come from calculations performed by Lee and Lin (2018). The metropolitan characteristics are used to examine correlations with freeway disamenities and to estimate the effect of freeway disamenities on metropolitan population growth.

The results are shown in Table 2. In each regression, the dependent variable is the disamenity measure, where a larger value represents lower average utility relative to the

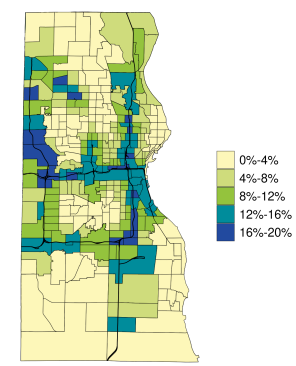
Figure 3: Neighborhood change and disamenities in Milwaukee



(a) Population Density 1950



(b) Population Density 2019



(c) Freeway Disamenities

This figure shows the relationship between freeway disamenities and population change in Milwaukee, Wisconsin. Panel (a) shows the population density in 1950, panel (b) shows the population density in 2019, and panel (c)shows the disamenities arising from freeways calculated from the calibrated structural model.

Table 2: Determinants of Disamenities

	Dependent variable:			
	Disamenities			
	(1)	(2)	(3)	(4)
ln(Pop. 1950)	0.007***	0.004***	0.005***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
ln(Resident Distance to CBD)		−0.032***		−0.024***
		(0.008)		(0.008)
ln(Employee Distance to CBD)		0.019***		0.013**
		(0.006)		(0.006)
ln(3 Mile Radius)		0.001***		0.001***
		(0.0003)		(0.0003)
ln(Total Miles)		0.005***		0.006***
		(0.001)		(0.001)
ln(Average Slope)			0.002	0.002
			(0.002)	(0.002)
Coastline: Y			0.006***	0.007***
			(0.002)	(0.002)
Region: NE			−0.005	−0.004
			(0.003)	(0.003)
Region: S			−0.011***	−0.008***
			(0.003)	(0.002)
Region: W			−0.005*	−0.002
			(0.003)	(0.003)
Constant	−0.046***	−0.019*	−0.026**	−0.006
	(0.011)	(0.011)	(0.012)	(0.012)
Observations	167	167	167	167
R^2	0.245	0.465	0.342	0.542
Adjusted R^2	0.240	0.448	0.317	0.512

This table shows the results of regression of the disamenity measure on various city characteristics. All regressions use ordinary least squares regressions. *p<0.1; **p<0.05; ***p<0.01

counterfactual simulation with complete mitigation. In column (1), the disamenity measure is regressed on the initial log population in 1950. The coefficient indicates that higher initial population is associated with larger disutility from freeways. This is consistent with the idea that in mature cities, where freeways had to be retrofitted, the implementation of the freeway program was more suboptimal, given that neighborhoods and employment centers were already established. Newer cities that were built after freeway construction had the advantage of developing around the freeways to avoid negative quality of life effects. This is not to suggest that the freeway network is more optimal, just that conditional on freeways, employment and residential population was more efficiently allocated.

In column (2), the measure is regressed on several characteristics of cities related to the location and scale of the freeway network and the location of residential population and employment. The variable "Resident Distance to CBD" measures the average distance of a resident to the central business district and conditional on city size and provides a measure of how centralized population is in each city.[8] Similarly, the variable "Employee Distance to CBD" measures the average distance of a worker to the central business district. Cities with more decentralized population are associated with lower estimated disamenities, which is intuitive since fewer residents are exposed to centrally located freeways. Cities with more decentralized employment are associated with larger estimated disamenities. The mechanism underlying this relationship is less clear, but one possibility is that concentrated employment makes it easier to route freeways to major employment centers while avoiding residential neighborhoods.

Network intensity and central placement are positively associated with estimated disamenities. These relationships are partly mechanical: the constructed measure rises when more freeway exposure intersects populated locations. Conditional on total mileage, central freeway mileage also indicates where the network lies relative to dense residential locations.

[8] Measures of residential and employment centralization are constructed using contemporary data, as comparable tract-level employment data and complete tract-level population data are generally unavailable for 1950. We interpret these variables as proxies for the underlying degree of centralization during the Interstate Highway era.

These coefficients describe the construction of the measure as well as cross-city differences in network configuration.

The regression in Column (3), illustrates the relationship between freeway disamenities and geographic features. "Coastline" is an indicator for whether or not a city is located on a coast. The positive coefficient indicates that coastal cities experience larger disamenties from freeways than other cities. This may arise from less flexibility in freeway construction from geographic constraints or from a higher correlation between jobs and residential amenities due to the higher desirability of coasts for both residential and production uses. The variable "Average Slope" is the population-weighted average slope in each metropolitan area. In this case, the correlation is positive but not statistically significant. Finally, indicator variables for each of the four regions are included, with the Midwest as the omitted region. The Midwest followed by the Northeast have significantly larger disamenities from freeways than the South. Cities in these regions were largely developed earlier and often before the onset of freeway construction. The South, on the other hand, exhibits lower disamenties and experienced a majority of its population growth in the later part of the twentieth century. Freeway construction in the South may have been less disruptive to already established dense urban neighborhoods, and development was able to more efficiently adjust to the location of freeways. Column (4) shows the results with all variables included.

Estimated disamenities are largest where highway construction intersected dense established neighborhoods and geographic constraints limited routing alternatives. The four groups of city characteristics examined here collectively capture these conditions. Their associations with estimated disamenities do not identify causal effects of any individual factor, but document a coherent pattern consistent with the routing-tradeoff mechanism: cities where separating freeways from residential neighborhoods was hardest show the largest estimated quality-of-life costs.

7 Conclusion

The Interstate Highway System generated large aggregate access benefits, but the costs of access were substantial. Cities with larger estimated freeway disamenities grew more slowly over 1950–2019, conditioning on total freeway mileage and initial population: a one-percentage-point increase in estimated utility loss is associated with 8.5 percent slower population growth. The mean estimated loss is 3.8 percent, with a standard deviation of 1.5 percent across cities. Total freeway mileage is positively associated with growth in the same specification. The net effect of the Interstate System on any given metropolitan area reflected both forces operating simultaneously.

Cross-city variation in disamenities reflects the routing tradeoff planners faced when building through established urban areas. Cities where dense pre-Interstate settlement, centralized employment, and geographic constraints offered little flexibility to avoid residential neighborhoods accumulated the largest quality-of-life losses. The same features that made urban freeways most valuable for access — proximity to concentrated labor markets — also made their disamenity costs most severe. The legacy costs of the Interstate era were highest precisely where the access gains were also largest.

These city-level measures open several directions. Sharper separation of the access and amenity channels would also strengthen the welfare interpretation: the current approach pairs a mileage proxy correlated with both against the model-based disamenity measure. A dynamic extension that traces the routing tradeoff as cities adjusted over the Interstate era would more cleanly separate the disamenity effect from equilibrium sorting responses. Alternatively, the growing wave of removal, capping, and burial proposals — from Milwaukee's I-794 to corridors across the Northeast and West Coast — provides a natural laboratory for cleaner identification by changing disamenities while preserving travel times. Cities where these measures are largest are where the case for mitigation is strongest and where empirical follow-up is most warranted.

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A Spatial model of freeway disamenities

In this section, we include a basic description of the quantitative structural model and calibration for ease of reference. Details and extensive discussion can be found in Brinkman and Lin (2024).

A city has J neighborhoods each with land area L_j that may be split between consumption and production. There are iceberg commuting costs $d_{jk} \equiv e^{\kappa \tau_{jk}}$, where τ_{jk} is the travel time between neighborhoods j and k, and κ describes the relationship between travel time and costs. We assume a closed city: total population N is fixed and expected utility is endogenous. This allows for comparison of counterfactual experiments in terms of expected utility.

Workers. Workers are homogeneous and have increasing preferences over consumption c, land l, and neighborhood amenities B_j.[9] Each worker m has an idiosyncratic preference $\nu_{jk,m}$ for a given home-work pair $\{j,k\}$, drawn from a Frechet distribution with shape parameter ε. Utility is $U_{jk,m}(c,l) = \nu_{jk,m} B_j \left(\frac{c}{\beta}\right)^{\beta} \left(\frac{l}{1-\beta}\right)^{1-\beta}$, where β is the consumption share of income. Workers earn a wage net of commuting costs $w_k/d_{j,k}$. The workers' budget constraint is then $\frac{w_k}{d_{jk}} = lq_j + c$, where q_j is the price of land at place of residence j. Maximizing utility conditioned on wages and rents yields indirect utility for each commuting pair: $V_{jk,m}(w_k, q_j) = \nu_{jk,m} \frac{w_k}{d_{jk}} B_j q_j^{(\beta-1)}$.

Individual workers choose a residence and workplace that maximizes utility. The probability that a worker will live in j and work in k is given by

$$\pi_{jk} = \frac{\left(d_{jk} q_j^{1-\beta}\right)^{-\varepsilon} (B_j w_k)^{\varepsilon}}{\sum_{j'=1}^{J} \sum_{k'=1}^{J} \left(d_{j'k'} q_{j'}^{1-\beta}\right)^{-\varepsilon} (B_{j'} w_{k'})^{\varepsilon}}, \tag{3}$$

and the probability that a worker will commute to k conditioned on living in j is

$$\pi_{jk|j} = \frac{\left(\frac{w_k}{d_{jk}}\right)^{\varepsilon}}{\sum_{k'=1}^{J} \left(\frac{w_{k'}}{d_{jk'}}\right)^{\varepsilon}}.$$

[9] We assume direct consumption of land. This is equivalent to assuming mobile capital and a Cobb-Douglas form.

This implies the commuting market clearing condition

$$N_{Wk} = \sum_{j=1}^{J} \left[\frac{\left(\frac{w_k}{d_{jk}}\right)^{\varepsilon}}{\sum\limits_{k'=1}^{J} \left(\frac{w_{k'}}{d_{jk'}}\right)^{\varepsilon}} N_{Rj} \right], \tag{4}$$

where N_{Wk} is the measure of workers working in k and N_{Rj} is the measure of workers residing in j. Total residential land consumption is the sum of land demand by all workers choosing j:

$$L_{Rj} = (1-\beta) \frac{N_{Rj}}{q_j} \sum_{k=1}^{J} \pi_{jk|j} \frac{w_k}{d_{jk}}. \tag{5}$$

Finally, expected utility is

$$E[u] = \Gamma\left(\frac{\varepsilon-1}{\varepsilon}\right) \left[\sum_{j'=1}^{J} \sum_{k'=1}^{J} \left(d_{j'k'} q_{j'}^{1-\beta}\right)^{-\varepsilon} (B_{j'} w_{k'})^{\varepsilon} \right]^{1/\varepsilon}. \tag{6}$$

Freeway disamenities. B_j represents nearly all neighborhood amenities, including natural factors such as beaches and endogenous factors such as schools, shopping, or safety. The exception is job accessibility, which is handled explicitly by the commuting structure of the model. We assume $B_j = b_j g(\delta_{Fj})$, where $g(\delta_{Fj})$ describes the disamenity at a given distance to the freeway, δ_{Fj} and is given by,

$$g(\delta_{Fj}) = 1 - b_F e^{-\eta \delta_{Fj}}, \tag{7}$$

where b_F is the size of the disamenity and η describes its spatial attenuation.

Production. A single final good is costlessly traded and produced under constant returns and perfect competition according to $Y_k = A_k L_{Wk}^{1-\alpha} N_{Wk}^{\alpha}$ in each location, where A_k is an exogenous total factor productivity, L_{Wk} is total land used for production, N_{Wk} is total employment, and α is the labor share in production. Profit maximization yields total commercial land use in each location:

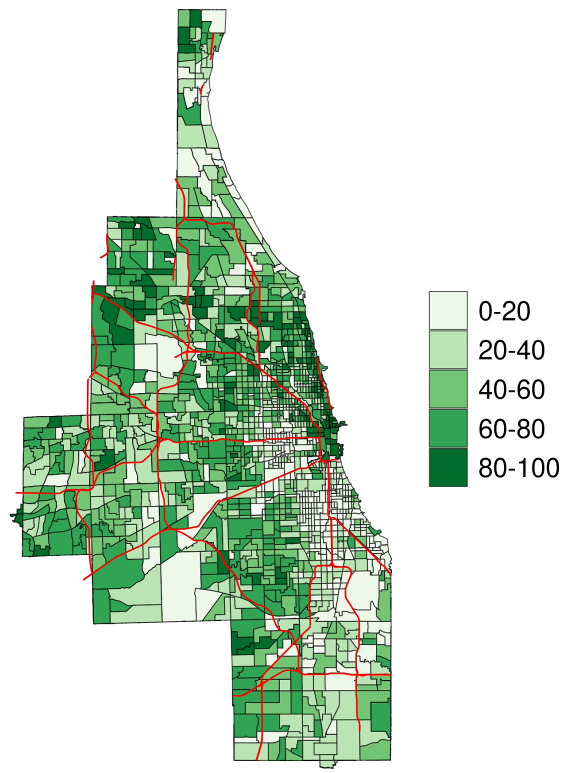
$$L_{W_k} = N_{W_k} \frac{(1-\alpha)}{\alpha} \frac{w_k}{q_j}. \tag{8}$$

Equilibrium. Assume that land area and travel costs $\{L_j, d_{jk}\}$ and total population N are exogenous; we observe these in the data. Also, values for the model's parameters $\{\alpha, \beta, \varepsilon\}$ and location fundamentals, $\{A_k, B_j\}$, are known. Then, equilibrium is a vector of prices $\{q_j, w_j\}$ and a vector of quantities, $\{N_{Hj}, N_{Wk}, L_{Hj}, L_{Wj}\}$ such that: (i) labor markets clear through commuting (equation 4), (ii) land markets clear in each location (equations 5 and 8), and (iii) total population equals N.

Calibration. For each city, we use the calibrated model to recover location-specific amenities B_j and productivities A_k by matching population and employment at the census tract level. The calibration and computation of the model follow Brinkman and Lin (2024), which provides more complete description of methods. The global parameters of the model are calibrated based on estimates in the literature. Specifically, we set the consumption share to $\beta = 0.94$, the labor share in production to $\alpha = 0.97$, time value of commuting parameter to $\kappa = 0.005$, and the Frechet shape parameter $\epsilon = 3.8$. With these parameters fixed, location characteristics are exactly identified using data on employment, residential population, land areas, and travel times. We then separate the neighborhood amenity b_j from the freeway disamenity by setting $b_f = 0.184$ and $\eta = 1.237$. These parameters are taken from Brinkman and Lin (2024), who estimated freeway disamenities in Chicago by recovering tract-level amenities from observed population, employment, and travel times and fitting an exponential decay function to the relationship between amenities and distance to freeways. For reference, the map of calibrated neighborhood amenities is shown in figure 4.

We perform a counterfactual simulation for each city where the disamenities from freeways are completely mitigated, but travel times remain the same. Mechanically, we adjust the location amenities by setting the disamenity parameter b_f to zero and then resolve the equilibrium and calculate expected utility. The difference in log utility between the counter-

Figure 4: Calibrated neighborhood amenities for Chicago



This figure shows the calibrated amenities for neighborhoods in Chicago derived from 2019 LODES data.

factual simulation and the baseline calibration provides a measure of freeway disamenities for each city by calculating the change in expected utility with total disamenity mitigation.

B Metropolitan Disamenity Measures

Table 3: Ranked Freeway Disamenity Measures by Metropolitan Area (Ranks 1–50)

Rank	Metropolitan Area	Disamenity (%)
1	San Diego–Chula Vista–Carlsbad, CA	7.69
2	Bridgeport–Stamford–Norwalk, CT	7.69
3	San Francisco–Oakland–Berkeley, CA	7.57
4	New York–Newark–Jersey City, NY–NJ–PA	6.76
5	Los Angeles–Long Beach–Anaheim, CA	6.67
6	Amarillo, TX	6.46
7	Milwaukee–Waukesha, WI	6.19
8	Buffalo–Cheektowaga, NY	6.08
9	Las Vegas–Henderson–Paradise, NV	5.97
10	Hartford–East Hartford–Middletown, CT	5.96
11	Cleveland–Elyria, OH	5.83
12	Providence–Warwick, RI–MA	5.75
13	New Haven–Milford, CT	5.72
14	Lansing–East Lansing, MI	5.66
15	Sacramento–Roseville–Folsom, CA	5.65
16	Ann Arbor, MI	5.55
17	Chicago–Naperville–Elgin, IL–IN–WI	5.50
18	Vallejo, CA	5.45
19	Toledo, OH	5.44
20	Baltimore–Columbia–Towson, MD	5.33
21	Albany–Schenectady–Troy, NY	5.27
22	Davenport–Moline–Rock Island, IA–IL	5.23
23	Harrisburg–Carlisle, PA	5.23
24	Riverside–San Bernardino–Ontario, CA	5.21
25	Rochester, NY	5.17
26	Topeka, KS	5.11
27	Akron, OH	5.05
28	Peoria, IL	5.03
29	Fargo, ND–MN	4.99
30	Portland–Vancouver–Hillsboro, OR–WA	4.99
31	Denver–Aurora–Lakewood, CO	4.98
32	Richmond, VA	4.97
33	Bellingham, WA	4.96
34	Kansas City, MO–KS	4.91
35	Louisville/Jefferson County, KY–IN	4.89
36	Springfield, MA	4.88
37	Flint, MI	4.80
38	Salt Lake City, UT	4.80
39	Fresno, CA	4.78
40	St. Louis, MO–IL	4.78
41	Virginia Beach–Norfolk–Newport News, VA–NC	4.76
42	New Orleans–Metairie, LA	4.73
43	Trenton–Princeton, NJ	4.71
44	Syracuse, NY	4.70
45	Indianapolis–Carmel–Anderson, IN	4.69
46	Minneapolis–St. Paul–Bloomington, MN–WI	4.67
47	Wichita, KS	4.65
48	Burlington–South Burlington, VT	4.63
49	Worcester, MA–CT	4.54
50	Columbus, OH	4.49

Table 4: Ranked Freeway Disamenity Measures by Metropolitan Area (Ranks 51–106)

Rank	Metropolitan Area	Disamenity (%)
51	Omaha–Council Bluffs, NE–IA	4.48
52	Boston–Cambridge–Newton, MA–NH	4.47
53	Laredo, TX	4.45
54	Oklahoma City, OK	4.44
55	Hagerstown–Martinsburg, MD–WV	4.36
56	Albuquerque, NM	4.36
57	Rockford, IL	4.34
58	Sioux Falls, SD	4.27
59	Seattle–Tacoma–Bellevue, WA	4.26
60	Macon–Bibb County, GA	4.25
61	Kalamazoo–Portage, MI	4.23
62	Detroit–Warren–Dearborn, MI	4.15
63	Des Moines–West Des Moines, IA	4.11
64	Roanoke, VA	4.08
65	Washington–Arlington–Alexandria, DC–VA–MD–WV	4.07
66	Ogden–Clearfield, UT	4.07
67	San Antonio–New Braunfels, TX	4.02
68	Little Rock–North Little Rock–Conway, AR	4.00
69	Cincinnati, OH–KY–IN	3.99
70	Miami–Fort Lauderdale–Pompano Beach, FL	3.98
71	Youngstown–Warren–Boardman, OH–PA	3.98
72	Shreveport–Bossier City, LA	3.96
73	Charleston, WV	3.94
74	Tulsa, OK	3.94
75	Birmingham–Hoover, AL	3.93
76	South Bend–Mishawaka, IN–MI	3.90
77	Norwich–New London, CT	3.89
78	Jacksonville, FL	3.87
79	Columbia, SC	3.82
80	Asheville, NC	3.82
81	Charleston–North Charleston, SC	3.81
82	Scranton—-Wilkes–Barre, PA	3.79
83	Stockton, CA	3.77
84	Charlotte–Concord–Gastonia, NC–SC	3.75
85	Salem, OR	3.71
86	Portland–South Portland, ME	3.71
87	Provo–Orem, UT	3.67
88	Waco, TX	3.67
89	Philadelphia–Camden–Wilmington, PA–NJ–DE–MD	3.66
90	Winston–Salem, NC	3.63
91	Jackson, MS	3.60
92	Durham–Chapel Hill, NC	3.59
93	Manchester–Nashua, NH	3.55
94	Fort Wayne, IN	3.54
95	Visalia, CA	3.53
96	Savannah, GA	3.47
97	Kingsport–Bristol, TN–VA	3.46
98	Knoxville, TN	3.44
99	Lincoln, NE	3.39
100	Erie, PA	3.38
101	Nashville–Davidson—-Murfreesboro—-Franklin, TN	3.32
102	Binghamton, NY	3.32
103	Pittsburgh, PA	3.25
104	Memphis, TN–MS–AR	3.25
105	Dallas–Fort Worth–Arlington, TX	3.21
106	Montgomery, AL	3.18

Table 5: Ranked Freeway Disamenity Measures by Metropolitan Area (Ranks 107–162)

Rank	Metropolitan Area	Disamenity (%)
107	York–Hanover, PA	3.16
108	Baton Rouge, LA	3.13
109	Springfield, MO	3.12
110	Atlanta–Sandy Springs–Alpharetta, GA	3.11
111	Orlando–Kissimmee–Sanford, FL	3.08
112	Reno, NV	3.07
113	Spartanburg, SC	3.07
114	Grand Rapids–Kentwood, MI	3.06
115	Austin–Round Rock–Georgetown, TX	3.06
116	Fort Smith, AR–OK	3.04
117	Columbus, GA–AL	2.99
118	Chattanooga, TN–GA	2.99
119	Raleigh–Cary, NC	2.96
120	Mobile, AL	2.92
121	Olympia–Lacey–Tumwater, WA	2.88
122	Pensacola–Ferry Pass–Brent, FL	2.85
123	Allentown–Bethlehem–Easton, PA–NJ	2.75
124	Eugene–Springfield, OR	2.72
125	Tuscaloosa, AL	2.70
126	Spokane–Spokane Valley, WA	2.63
127	Tucson, AZ	2.62
128	Huntington–Ashland, WV–KY–OH	2.61
129	Gulfport–Biloxi, MS	2.60
130	Boise City, ID	2.59
131	Tampa–St. Petersburg–Clearwater, FL	2.59
132	Colorado Springs, CO	2.53
133	Augusta–Richmond County, GA–SC	2.39
134	Greensboro–High Point, NC	2.38
135	Crestview–Fort Walton Beach–Destin, FL	2.38
136	Greenville–Anderson, SC	2.32
137	Utica–Rome, NY	2.32
138	Poughkeepsie–Newburgh–Middletown, NY	2.24
139	Houston–The Woodlands–Sugar Land, TX	2.23
140	Palm Bay–Melbourne–Titusville, FL	2.21
141	Reading, PA	2.20
142	Port St. Lucie, FL	2.18
143	Lexington–Fayette, KY	2.15
144	Tallahassee, FL	2.11
145	Gainesville, FL	2.03
146	Canton–Massillon, OH	1.92
147	Fayetteville, NC	1.84
148	Phoenix–Mesa–Chandler, AZ	1.83
149	Deltona–Daytona Beach–Ormond Beach, FL	1.77
150	Lafayette, LA	1.76
151	Madison, WI	1.64
152	Huntsville, AL	1.60
153	Beaumont–Port Arthur, TX	1.45
154	Fort Collins, CO	1.42
155	Killeen–Temple, TX	1.27
156	Longview, TX	1.25
157	Hickory–Lenoir–Morganton, NC	1.22
158	Bakersfield, CA	1.05
159	Tyler, TX	0.98
160	Lakeland–Winter Haven, FL	0.77
161	Ocala, FL	0.66
162	Boulder, CO	0.29