More Roads or Public Transit?
Insights from Measuring City-Center Accessibility*

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First Version: November 2022
This Version: February 2023

Abstract

We propose a theory-inspired measure of the accessibility of a city's center: the size of the surrounding area from which it can be reached within a specific time. Using publicly available optimal-routing software, we compute these "accessibility zones" for the 109 largest US and European cities, separately for cars and public transit commutes. Compared with European cities, US cities are half as accessible via public transit and twice as accessible via cars. Car accessibility zones are always larger than public transit zones, making US cities more accessible overall. But this creates tradeoffs: car-oriented cities have less green space, more congestion, and worse health and pollution externalities.

*We thank Nishi Felton, Matthew Murillo, and Ephraim Sutherland for outstanding research assistance. We also thank Victor Couture, Gilles Duranton, and the audience at the NBER working group meeting on "Transportation Economics in the 21st Century" for insightful comments.

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1. INTRODUCTION

The central business districts (CBDs) of its largest cities account for an outsized share of the United States' economic growth (Moretti, 2012; Ahlfeldt et al., 2020; Eckert et al., 2022). Broadening commuting access to these areas is an important policy objective and requires either housing investments near the CBD or improved transportation infrastructure to allow workers from farther afield to commute in. Expanding housing supply near CBDs has proven difficult due to political resistance, regulations, and land-use restrictions (Hsieh and Moretti, 2019; Ganong and Shoag, 2017). Such difficulties raise the stakes for designing effective transportation policies.

The fact that much of the US highway infrastructure constructed after World War II is now approaching their expiration dates (New York Times, Feb. 11, 2022) also opens a rare political window to change the *type* of transportation systems US cities rely on. Should the U.S. repair crumbling roads and highways to enhance car-based mobility or replace them with new public transit infrastructure that re-orients U.S. commuting systems away from their current car dependence?

This paper proposes new measures of CBD accessibility by cars and by public transit, discusses their construction and interpretation, and uses them to inform this transportation debate. We define "accessibility zones" as the size of the surrounding areas from which the CBD can be accessed within a given time window by either car or public transit. We show how our measures are related to commuting efficiency, when interpreted through the lens of the canonical quantitative model of commuting (Monte et al., 2018; Ahlfeldt et al., 2015; Redding and Rossi-Hansberg, 2017). In that framework, larger accessibility zones are associated with higher overall city productivity, for any given distribution of origin, destination, and mode choices of workers.

Accessibility zones are easy to construct for most cities worldwide using standard travel-routing software. Using Google-maps-style route-planning software, we compute the accessibility-zone areas of the 109 largest US and European cities. In particular, we separately compute the areas around cities' CBDs accessible within 0-15, 15-30, 30-45, and 45-60 minutes for public transit and car-based commutes during Wednesday morning rush hour. We use the resulting dataset to establish a set of facts about the accessibility of those cities' CBDs.

First, public transit accessibility zones are almost twice as large in European cities relative to comparably sized US cities for any specific time distance. For example, the average size of the area from which CBDs of US cities can be reached within 15-30 minutes by public transit is 34 square kilometers, compared with almost 63 square kilometers in the average European city in our sample.

Second, car accessibility zones are 2.7 times larger in US cities than in Europe for commutes between 15 and 30 minutes, and that gap is even larger for commutes within 15 minutes. The average US city in our sample boasts 1,160 square kilometers from which the CBD can be reached within 15-30 minutes by car; the same area is only 430 square kilometers in Europe.

Third, US cities' public transit accessibility disadvantage appears less severe than what informal public discourse often suggests. Although public transit is generally faster and more widespread in Europe, U.S. cities' bus-based public transit provision is often relatively effective because it uses the superior road infrastructure that serves cars. Small European cities have a particularly pronounced public transit advantage over smaller US cities.

Fourth, on average, car accessibility zones are almost an order of magnitude larger than public transit accessibility zones in both Europe and the US. As a result, US cities outperform Europe in terms of *overall accessibility*, given the relative strength of their car-based commuting systems. The significant investments made in infrastructure to support car-based mobility allow US commuters to lose less in time and productivity than their European counterparts.

Fifth, we show that supporting car commutes creates some tradeoffs. It forces US cities to allocate more space to car-related infrastructure, resulting in a loss in amenities to residents. US cities offer much less green space within city boundaries than European cities.

Sixth, US cities' car-oriented urban design is associated with additional negative externalities. A comparison of the accessibility-zone areas during weekday rush hour and Sunday evening shows heavy car usage slows down everyone's commutes, due to congestion. Conversely, broad transit usage during rush hour *speeds up* commutes, which is likely related to the economies of scale in public transit provision. Car orientation of cities is also associated with worse air pollution, less walking and biking, a larger share of physically inactive people, obesity, cardiovascular and respiratory diseases, and lower life expectancy.

We also combine our accessibility measures with the structure of a quantitative commuting model to conduct a set of partial-equilibrium counterfactuals. We use that framework to ask, "What would the increase in city productivity be if a city's accessibility-zone area increased by 10%, holding location and mode choices of agents fixed at their values observed in the data?"

We find enlarging accessibility-zone areas is subject to decreasing returns. Because population density falls off from city centers in most cities, each additional accessible square kilometer tends to contain fewer additional commuters. Increasing public transit accessibility-zone areas is more ineffective than increasing car areas, because public transit usage declines at the expense of car usage as people move farther away from the CBD. Increasing the size of transit accessibility zones has minimal effects on city productivity in all but the largest US cities, given the generally low transit usage in most cities.

In the long run, general-equilibrium adjustments in mode and location choices could change these predictions. In particular, policies that enlarge accessibility zones would be more effective if workers' location, mode, and destination choices respond.

Overall, our empirical results highlight a crucial tradeoff. US transportation systems are generally more effective at bringing workers from city outskirts into the CBD than most systems in European cities. However, this (car-based) commuting-efficiency advantage of US cities comes at a cost to public health and the environment. Our accessibility measure provides a valuable empirical tool for researchers and policymakers to analyze these tradeoffs quantitatively to inform future transportation policy choices.

Related Literature. Our main contribution is a new measure of infrastructure-enabled CBD accessibility. A closely related literature in urban planning has studied various notions of urban access beginning with Hansen (1959) and Ingram (1971). The most widely used measure of "access" in this literature is the average commuting time between workers' residences and their job locations in a city (Wu and Levinson, 2020; Bento et al., 2005). These measures combine (a) the location choices of firms and workers, (b) the travel-mode choices of workers, and (c) the efficacy of the transportation system to facilitate commutes for each mode. By contrast, our "accessibility zones" conceptually separate the efficiency of the commuting system from the *choices* of firms and workers.

Our approach relies on information on the estimated travel times between arbitrary points, using all available transportation infrastructure. An emerging literature in urban economics imports software companies' navigation and route-finding tools to study urban mobility. In pioneering work, Akbar et al. (2021) and Couture et al. (2018) use Google maps' route-finding feature to measure car travel speeds at different times of the day in the US and in India. Kreindler (2022) measures traffic density using GPS records of trips collected via a smartphone app. Miyauchi et al. (2021) use smartphones' GPS data for Japan to show to establish new facts about travel patterns within cities. Our approach is related but different: we combine optimal route planning with an algorithm to aggregate points into areas that fall below a certain travel-time threshold.

A broad class of quantitative spatial models of commuting combines commuting costs, mode choices, and the spatial distribution of workers and firms into one "sufficient statistic measure of realized equilibrium commuting access" (e.g., Monte et al., 2018; Tsivanidis, 2022). We show how to decompose this "commuting access" measure into an easy-to-compute statistic on the efficiency of the commuting system – independent of the commuting and residential choices of workers.

The paper has the following structure. In section 2, we provide a theoretical framework that motivates our accessibility measure and clarifies its interpretation. In section 3, we describe the construction of accessibility-zone areas in the data and present descriptive statistics of driving versus public transit in the US versus Europe. Section 4 discusses the relationship between accessibility-zone areas and land use, health, and environmental outcomes.

2. Theory

In this section, we motivate our accessibility-zone measure using a version of the canonical theoretical framework of commuting developed in Ahlfeldt et al. (2015), Monte et al. (2018), and Redding and Rossi-Hansberg (2017).

2.1 A Quantitative Model of Commuting

Setup. We consider a closed city economy inhabited by a mass $\bar{L}$ of agents. The city consists of $i = 1, ..., N$ neighborhoods. Neighborhoods differ in their residential amenities, B_i, labor productivity, Z_i, and mode-specific commuting times to other locations. Each agent chooses a residential location, a work location, and a commuting mode between the two.

Labor Demand. In each neighborhood, a representative firm produces the homogeneous final good using a labor-only technology, $Y_i = Z_i H_i$, where H_i is the total units of labor used in location i. Input and output markets are competitive; trade is free. As a result, the final good's price is constant across locations; we choose it as the numeraire. The wage per unit of labor in neighborhood i is then $w_i = Z_i$.

Labor Supply. Workers spend their entire income on the final good, enjoy amenities in their residential location, and earn income in their work location. Agents can supply a maximum of 1 unit of labor time in their workplace. Commuting between locations i and j via mode m costs a fraction $\tau_{ij}^m \in (0,1)$ of that time. The utility of a worker ω who lives in location i, works in location j, and commutes using mode m transportation is given by:

$$V_{ij}^m(\omega) = w_j(1-\tau_{ij}^m)B_i\eta_{ijm}^\omega,$$

where η_{ijm}^ω is a worker-specific preference shifter.

Aggregation. To facilitate aggregation, we assume agents draw their preference shifters for each location independently from identical Fréchet distributions, $F(\eta) = \exp\{-\eta^{-\kappa}\}$, where $\kappa > 0$ indexes the heterogeneity of tastes for a given workplace-residence-mode combination among agents. With this standard assumption, we can write the fraction of agents that live in location i and work in j and commute via mode m by ϕ_{ij}^m, so that

$$\phi_{ij}^m = \frac{(B_i(1-\tau_{ij}^m)Z_j)^\kappa}{\sum_{i,j,m}(B_i(1-\tau_{ij}^m)Z_j)^\kappa}. \tag{1}$$

We can then solve for the number of workers living in neighborhood i, L_i, and the units of labor supplied to work in location j, H_j:

$$L_i = \sum_{j,m}\phi_{ij}^m\bar{L} \quad \text{and} \quad H_j = \sum_{i,m}(1-\tau_{ij}^m)\phi_{ij}^m\bar{L}.$$

2.2 Commuting to Central Business Districts

We define the city's CBD as the location with the highest productivity. We index the CBD location with $j^* = \arg\max\{Z_j\}$. Equilibrium labor supply to the CBD can be written as follows:

$$H_{j^*} = \bar{L}\sum_m \sum_i \phi^m_{ij^*}(1-\tau^m_{ij^*}) = \bar{L}\sum_m \Theta^m_{j^*} = \bar{L}\Theta_{j^*} \tag{2}$$

where the term $\Theta_{j^*} \in (0,1)$ measures the fraction of labor supply employed in the CBD in equilibrium, and $\Theta^m_{j^*} \in (0,1)$ is the fraction of labor supplied to the CBD via mode m. We refer to $\Theta_{j^*} \in (0,1)$ as the commuting efficiency of the city, and to $\Theta^m_{j^*}$ as the contribution of mode m to overall commuting efficiency. The term Θ_{j^*} also has an intuitive interpretation as the fraction of potential labor supply that is allocated to the most productive location, the CBD, in equilibrium; as a result, we also refer to it as CBD labor supply.

Average income per capita in the city is $\bar{W} = \Theta_{j^*}Z_{j^*} + (1-\Theta_{j^*})\bar{Z}_{j\neq j^*}$, where $\bar{Z}_{j\neq j^*}$ is a weighted average of the productivity in non-CBD locations. Whenever all agents work in the CBD ($\sum_{i,m}\phi^m_{ij^*} = 1$) and commuting into the CBD is costless ($\tau^m_{ij^*} = 0 \forall\, i, m$), labor supply to the CBD achieves its full potential, that is, $\Theta_{j^*} = 1$ so that $H_{j^*} = \bar{L}$, and average income per capita is maximized at Z_{j^*}.

In our theory, indidvidual-specific preferences for workplace-residence-mode combinations imply that even if commuting is costless, some workers choose to work in less productive locations than the CBD so that $\Theta_{j^*} < 1$. When personal preferences vanish ($\kappa \to \infty$), all agents work where the wage net of commuting costs and amenities is highest. In this limit case, Θ_{j^*} is a strictly declining function of commuting costs into the CBD from any origin; welfare is maximized when these costs are zero so that $\Theta_{j^*} = 1$. The economy without personal route preferences provides a natural theoretical benchmark.

2.3 A New Measure of CBD Accessibility

Equations 1 and 2 highlight that equilibrium labor supply into the CBD depends on commuting infrastructure (τ^m_{ij}), commuting mode choices, and the residential locations of workers. In reality, transportation infrastructure improvements require very different policy approaches from attempts to alter mode choices or the residential location decisions of workers. As a result, we focus on transportation infrastructure and propose an empirically tractable measure of the effectiveness of a transportation system independent of workers' choices of residential locations and modes.

To move toward such a measure, we group neighborhoods based on the time required to reach the CBD from them, separately for each mode. In particular, we create sets of locations, $\mathcal{I}_{t,t+\Delta}$, for which the commuting time lies between t and $t+\Delta$ units of time: $\mathcal{I}_{t,t+\Delta} \equiv \{i : \tau_{ij^*} \in \{t, t+\Delta\}\}$. We refer to the collection of locations $\mathcal{I}^m_{t,t+\Delta}$ as $(t, t+\Delta)$-minute mode-m accessibility zones. We aggregate our expression for commuting efficiency to the level of $(t, t+\Delta)$ mode-m accessibility zones as follows:

$$H_{j^*} = \bar{L} \sum_{m,t} \phi^m_{tj^*}(1 - \bar{\tau}^m_{t,t+\Delta}) \text{ s.t. } \phi^m_{t,t+\Delta} = \sum_{i \in \mathcal{I}_{t,t+\Delta}} \phi^m_{ij^*};\ \bar{\tau}^m_{t,t+\Delta} = \sum_{i \in \mathcal{I}_{t,t+\Delta}} \frac{\phi^m_{ij^*}}{\phi^m_{t,t+\Delta}} \tau^m_{ij^*}$$

Our measures of CBD accessibility are the total areas of all locations in the $(t, t+\Delta)$ mode-m accessibility zone, which we denote $\mathcal{A}^m_{t,t+\Delta}$. Accessibility zones are an intuitive measure of the transportation system's contribution to commuting efficiency. To illustrate, we decompose our measure of commuting efficiency, Θ_{j^*}, defined in equation 2 as follows:

$$\Theta_{j^*} = \sum_{m,t} \mathcal{A}^m_{t,t+\Delta} \frac{\phi^m_{t,t+\Delta}}{\mathcal{A}^m_{t,t+\Delta}} (1 - \bar{\tau}^m_{t,t+\Delta}) = \sum_{m} \underbrace{\sum_{t} \mathcal{A}^m_{t,t+\Delta} \omega^m_{t,t+\Delta} (1 - \bar{\tau}^m_{t,t+\Delta})}_{\Theta^m_{j^*}}, \tag{3}$$

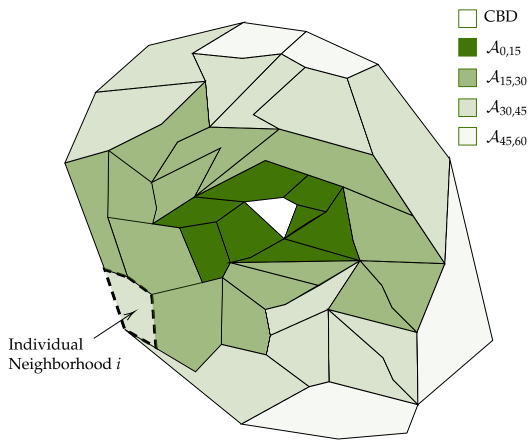
where t indexes the accessibility zones. The term $\omega^m_{t,t+\Delta}$ is the population density of agents within the accessibility zone that use mode m to commute to the CBD.[1] Note accessibility zones are additive, for example, $\mathcal{A}^m_{0,30} = \mathcal{A}^m_{0,15} + \mathcal{A}^m_{15,30}$.

Figure 1 shows an example of a city composed of neighborhoods grouped into different accessibility zones for a single mode. The black-lined polygons are neighborhoods which we indexed by i in our model, each associated with an average commuting time of τ_{ij^*} to the CBD. The central neighborhood is the CBD, which is the highest-productivity work location. The green shading indicates which neighborhood belongs to which accessibility zone given its commuting time to the CBD.

We opt for the decomposition in equation 3 for several reasons. First, accessibility-

[1] Note a location may be in accessibility zone t for mode m commutes but in accessibility zone t' for mode m' commutes, because m' is slower or faster than m.

FIGURE 1: AN EXAMPLE CITY WITH ACCESSIBILITY ZONES



Notes: The figure shows an example city. Each black-lined polygon corresponds to a neighborhood i. The central white neighborhood is the most productive, and is hence referred to as CBD. A neighborhood's shade of green indicates its associated accessibility zone. Accessibility zones are defined as the set of neighborhoods for which commuting times to the CBD are between t and $t + \Delta$ minutes.

zone areas, $\mathcal{A}^m_{t,t+\Delta}$, provide an objective measure of the efficiency of the city's commuting system *independent* of workers' decision regarding where to live and which mode to use - which are instead captured by $\omega^m_{t,t+\Delta}$.[2] Second, $\mathcal{A}^m_{t,t+\Delta}$ can be computed using publicly available software for almost all cities in the world. Third, the decomposition in equation 3 maps neatly into the different development strategies that policymakers can pursue to improve the CBD's total commuting access: (1) Improve transportation infrastructure to move workers from high-time-distance to low-time-distance accessibility zones; (2) improve transportation infrastructure to lower the average transportation cost within a given accessibility zone, $\bar{\tau}^m_{tj*}$; (3) build housing in low-time-distance accessibility zones ($\omega^m_{0,15}$); or (4) incentivize substitution toward modes with larger accessibility zones (also represented in $\omega^m_{t,t+\Delta}$).

Our paper focuses on measuring and describing $\mathcal{A}^m_{t,t+\Delta}$ for actual cities to generate insights that can inform critical transportation-policy questions. Have some US cities been more successful than others at creating large accessibility zones for their workers? How do accessibility zones compare across different modes of transport? Are US cities systematically worse at creating large accessibility zones than cities elsewhere? What can we learn from the cross-section of US cities about the societal implications of enlarging the accessibility zones for cars versus for public transit?

[2] In other words, $\mathcal{A}^m_{t,t+\Delta}$ is invariant to changes in agents' choices of modes or residence locations; it is only a function of τ^m_{ij*} $\forall i$.

The size of accessibility zones for a given city depends not only on the quality of the physical infrastructure (e.g., streets and rail tracks) but also on the utilization of these routes (e.g., through congestion) and the frequency and interoperability of different transit options. In the next section, we describe how we overcome these measurement challenges and present the accessibility-zone areas for a large sample of cities.

3. Accessibility-Zone Areas in the Data

This section describes our process for constructing accessibility zones for 109 large cities in the US and Europe. Tables C.3 and C.4 in the Appendix provide the complete list of cities. We use the accessibility-zone areas to derive a set of new facts about the efficiency of commuting systems in the US and Europe.

3.1 From Theory to Measurement

The vast majority of commutes in the cities in our sample occur via either public transit or car and take less than 60 minutes.[3] Accordingly, we focus our measurement on car ($m = C$) or public transit ($m = P$) commutes that take less than 60 minutes. We split the 60 minutes into four 15-minute intervals, so that the empirical exercise implements $t = 0, 15, 30, 45, 60$, and $\Delta = 15$ in equation 3. As a result, the empirical counterpart ($\tilde{\Theta}_{j^*}$) to the commuting-efficiency measure (Θ_{j^*}) in equation 3 can be written

$$\tilde{\Theta}_{j^*} = \sum_{t \in \{0,15,30,45\}} \mathcal{A}^C_{t,t+15} \omega^C_{t,t+15} (1 - \bar{\tau}^C_{t,t+15}) + \mathcal{A}^P_{t,t+15} \omega^P_{t,t+15} (1 - \bar{\tau}^P_{t,t+15}), \tag{4}$$

where $\Theta_{j^*} = \tilde{\Theta}_{j^*} + \xi$ and ξ captures CBD labor supply provided by modes other than cars and public transit, labor supply provided by commutes beyond 60 minutes via any mode, and measurement error.

3.2 Constructing Accessibility Zones

Our model defines the CBD as the location with the highest labor productivity. Data on location-specific productivity are generally not available for cities in

[3] Across all the US cities in our sample, 96% of commuters into the CBD use car or public transit; of those, only 12% have commutes above 60 minutes.

the US or around the world. Statistical agencies also generally do not provide a ready-to-use definition of the location of a city's CBD. We follow existing papers and define the center of the CBD as the latitude and longitude coordinates generated by feeding the city's name into Google's Geocoding Application Programming Interface (API) (see Holian and Kahn, 2012; Couture and Handbury, 2020; Couture et al., 2021).[4] We refer to the area that falls within a one-kilometer radius around these coordinates as the CBD. The median US CBD in our sample accounts for 28% of all employment within a 20 kilometer radius around the CBD. Seventy-seven percent of CBDs defined in this way include one of the top-three highest average income ZIP codes in the respective city.

The ubiquity of modern travel-routing software makes computing accessibility zones feasible for most major cities worldwide. Setting the destination to any point within the CBD, software such as Google Maps allows users to quickly find the fastest mode-specific route from any origin at any point in the day. An essential feature of such software for public transit is that it uses the actual schedules of all buses, trains, subways, and trams in making route-time predictions. For cars, it takes into account the actual traffic situation.

We first describe how one would use Google maps to construct accessibility zones, given most readers' familiarity with the tool. First, divide the city into parcels of land. The smaller the parcels, the more accurate the geographic delineations of each zone. Use Google Maps to compute the travel time between the centroid of each parcel and the closest point in the CBD, separately for car and public transit commutes. Then group parcels into accessibility zones, $\mathcal{I}^m_{t,t+\Delta}$, depending on the commute time to the CBD, within 0-15, 15-30, 30-45, or 45-60 minutes, separately for the two modes. Summing the area of all parcels within each time zone (e.g., 0-15) yields the total accessibility-zone area, $\mathcal{A}^m_{t,t+\Delta}$, defined in equation 4.[5]

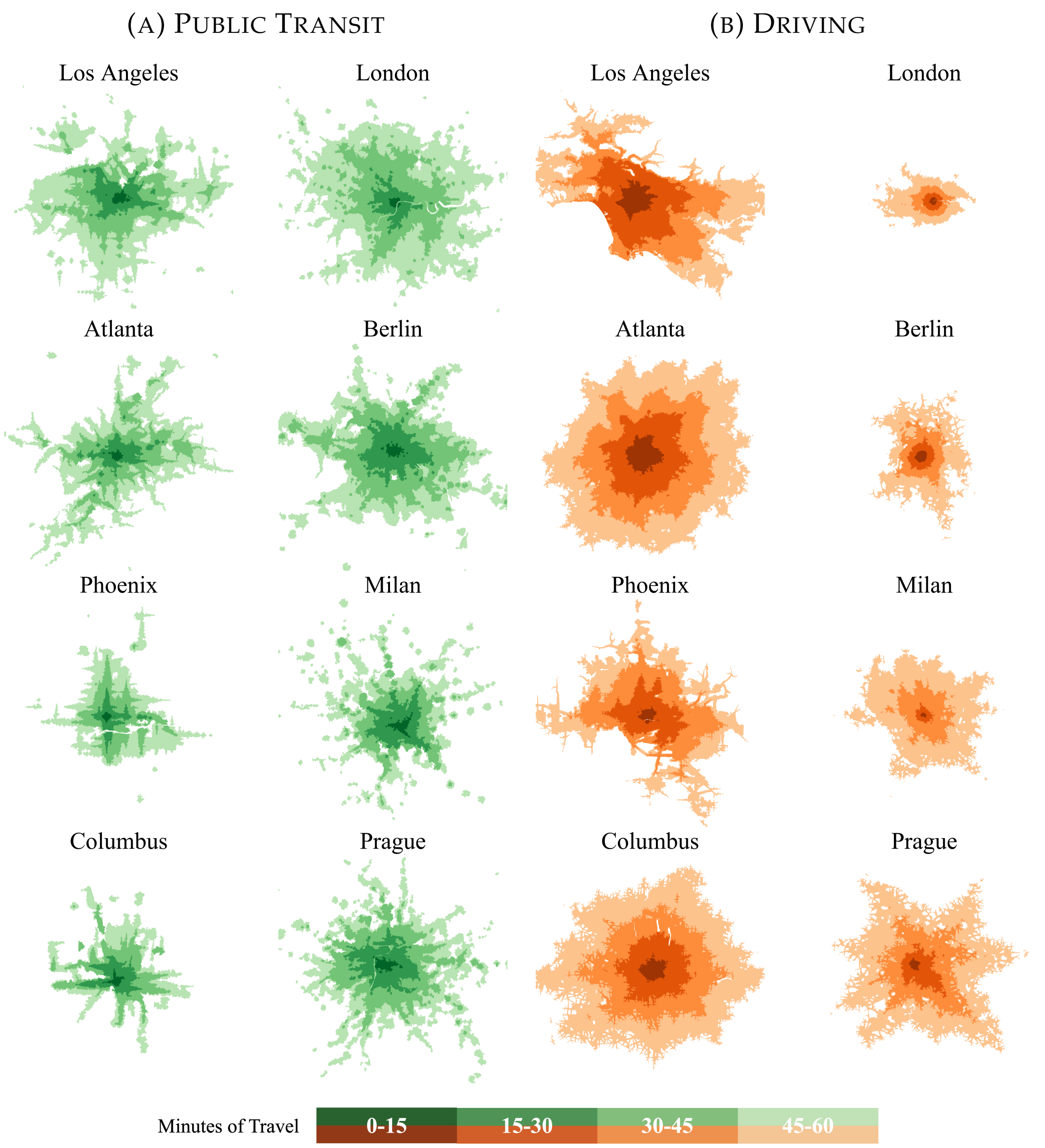
In practice, we use the interface of a software company called "Traveltime, Inc," which automates the process described above.[6] Traveltime's calculations

[4] Holian and Kahn (2012) report that "although this method of identifying CBDs places considerable trust in Google's potentially ad-hoc definitions of central places, we found them to be quite reasonable in all cases."

[5] Each parcel belongs to only one (mutually exclusive) accessibility zone within a mode. However, a parcel could be in the 30-minute zone for car commutes and the 15-minute zone for public transit commutes. Accessibility zones are not necessarily contiguous. For example, workers who live near subway stations can often reach the CBD faster than from other areas closer to the CBD in terms of their straight-line distance.

[6] See `https://app.traveltime.com/` for the web app to use this data product. The app works for any country for which online mapping services are available.

FIGURE 2: ACCESSIBILITY ZONE AREAS



Notes: The figure shows the area reachable from a city's CBD within 0-15, 15-30, 30-45, and 45-60 minutes ("accessibility zones") for four US and four European cities, with comparably sized cities placed next to each other. The left panel shows the accessibility zones for public transit commutes (green), and the right panel shows the accessibility zones for car-based commutes (orange) that arrive in the CBD at 8:45 AM on a Wednesday. The (0,15)-minute accessibility-zone area has the darkest, and the (45,60)-minute accessibility-zone area has the lightest hue. All accessibility zones appear on the same scale.

use publicly-available schedule data for public transit. All major cities' transit networks have public APIs that provide real-time information about arrival and departure times at any given hour of the day. The Traveltime algorithm accounts for waiting times, walking time to and from transit, and time spent traversing stations, using historic walking-speed data accounting for intersections and traffic signals. The algorithm also uses "OpenStreetMap," an open-source API that provides data on the complete road infrastructure and street-specific speed profiles for most countries. Our calculations account for traffic congestion patterns using Traveltime's algorithm and data, traffic lights, and the time required to park the car at the destination.

We use the Traveltime API to obtain the area from which the CBD of a given city can be reached within 15, 30, 45, and 60 minutes on Wednesday at 8 AM, separately for public transit users and drivers. We then subtract the (0,15)-minute area from the (0,30)-minute area to obtain the (15,30) accessibility-zone area and so on, to create the $\mathcal{A}^{m}_{t,t+\Delta}$ for all cities in our sample. An advantage of using Traveltime over Google Maps is that the former creates "smooth zones"; that is, creating a grid of locations and computing centroids.

We explore the robustness of the resulting accessibility zones to alternative construction procedures. First, we re-do our exercise using a different software provider, `https://www.targomo.com/`, which provides the same service. Second, instead of relying on the proprietary software of a company, we construct accessibility zones using the GoogleMaps API and Python.[7] Table A.1 in the Appendix shows the high correlation between the areas of accessibility zones constructed using the different approaches.

3.3 Comparing Accessibility across Modes and Countries

Figure 2 shows accessibility zones $\{\mathcal{A}^{m}_{t,t+\Delta}\}^{m=C,T}_{t=0,15,30,45}$ for a sample of cities. Public transit zones are shown in green in the two columns on the left, and car zones in orange on the right. Darker hues indicate shorter travel times. Comparable population-sized US and European cities are next to each other in the same row.

Figure 2 highlights four important patterns that generalize to the full sample of cities. First, US cities' car accessibility zones are generally larger than those of European cities with comparable population sizes. Second, the opposite is true for public transit zones. The European advantage in public transit is especially

[7] We use GoogleMaps API to obtain mode-specific travel times between any two points to perform a grid search over a given number of rays radiating outward from the destination. One starts at some given distance and then moves inward or outward along each ray until reaching the given time threshold, say, 60 minutes. The envelope of the final 60-minute points along each ray delineates one of our accessibility zones. This approach misses spatial discontinuities in access that are important for public transit, captured by the Traveltime algorithm.

TABLE 1: AVERAGE ACCESSIBILITY-ZONE AREAS BY REGION AND MODE IN SQUARE KILOMETERS

	Car			Public Transit			Car/Public Transit		
Min.	US	Europe	Ratio	US	Europe	Ratio	US	Europe	Ratio
0-15	213.17	40.67	5.24	4.01	6.83	0.59	62.19	7.88	7.89*
15-30	1159.94	428.23	2.71*	33.74	62.83	0.54***	47.49	8.77	5.41*
30-45	2292.72	1408.76	1.63***	102.68	170.07	0.60***	27.07	10.16	2.66
45-60	4302.56	3173.93	1.36***	167.06	287.44	0.58***	36.16	13.34	2.71**

Notes: This figure shows average accessibility-zone areas for various time intervals and modes in the US and Europe. The third column in the ”Car” and ”Public Transit” panels shows the ratio of the preceding two numbers in the respective row. The ”Car/Public Transit” panel shows the ratio of the car relative to public transit accessibility-zone areas (”car orientation”) for each time interval and region. The last panel's third column shows the ratio of US cities' car orientation relative to European cities' car orientation. We conducted Wald tests in all columns with a ”Ratio” header for the null hypothesis that the ratio equals 1. The number of stars indicates the p-value with the following interpretation: *** p<0.01, ** p<0.05, * p<0.1.

pronounced for short-distance commutes. Third, car accessibility zones in US cities are much larger than their corresponding public transit zones – but not necessarily in Europe, especially for longer commuting distances. Fourth, a comparison across all four columns in a row shows car accessibility zones in the US are the largest overall. The infrastructure supporting car travel in US cities affords the greatest “overall accessibility.”

Insights from the Full Sample. Table 1 shows the insights from Figure 2 generalize to the full sample of cities. The table shows the average accessibility-zone areas in square kilometers, separately by mode, region, and time distance. The “Car” panel on the left shows that, depending on the time distance, car accessibility zones are 1.4-5.2 times larger in the US than in Europe. The US car advantage is most pronounced for short commutes between 15 and 30 minutes, perhaps reflecting the difficulty of navigating the dense cores of old European cities by car. The “Public Transit” panel in the middle shows transit zones in US cities are only approximately 0.6 times the size of those of European cities, regardless of the commuting distance.

Table 1 also shows car travel offers larger overall accessibility across all time distances in both Europe and the US; that is $\mathcal{A}^C_{t,t+15} > \mathcal{A}^P_{t,t+15}\ \forall t \in \{0, 15, 30, 45\}$. A corollary of this finding is that US cities enjoy greater accessibility overall because they have a comparative advantage in car-based commutes.

Figure 2 highlights one reason why public transit systems provide less access to CBDs than cars. Especially at longer distances from the CBD, public transit provides ”patchy” access. Only people who live very close to the sparse network of transit stops in outlying parts of cities can quickly access the CBD. By contrast, car-based access is spatially more continuous. Note our accessibility zones focus on physical areas, not population. Housing and population may endogenously respond by densifying near transit stations (which is captured in ω in equations 3 and 4). Our accessibility measure tracks the physical space available to accommodate such responses.

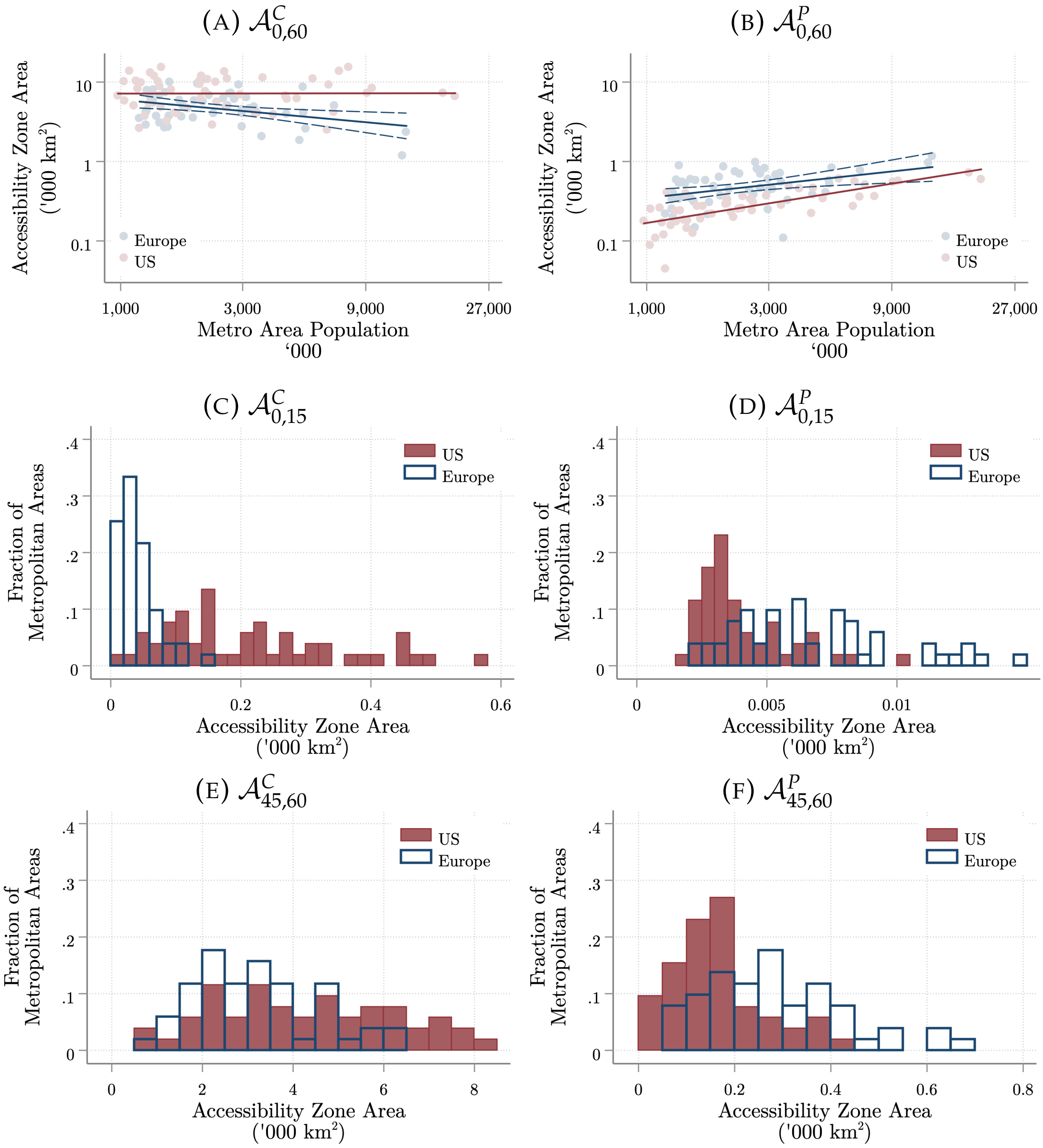
Variation Across Cities. The two panels in the top row of Figure 3 show the relationship between accessibility and city size. We graph the areas of the (0,60)-minute car accessibility zones, $\mathcal{A}^C_{0,60}$, and the (0,60)-minute public transit accessibility zones, $\mathcal{A}^P_{0,60}$, against city size, separately for the US and Europe. In the US, the size of car accessibility zones does not vary with city population. By contrast, car accessibility zones are smaller in larger European cities, perhaps because those larger cities are older, and their historical urban cores are dense, congestion-prone, and difficult for cars to navigate.

Public transit accessibility zone areas are increasing in city size on both continents, reflecting the economies of scale inherent in mass public transit, which has high fixed setup costs and low marginal costs for cities. A more extensive ridership base permits investments in larger transit systems, higher station density, and train frequency.

The other four panels show the distribution of $\{\mathcal{A}^C_{0,15}, \mathcal{A}^P_{0,15}, \mathcal{A}^C_{45,60}, \mathcal{A}^P_{45,60}\}$ across our samples of US and European cities. US and European cities are most dissimilar when focusing on (0,15)-minute accessibility zones. Most European cities have very small $\mathcal{A}^C_{0,15}$, and there is little heterogeneity. US cities differ widely in their (0,15) car accessibility areas, and almost all US cities have larger zones than European cities. Conversely, most European cities outperform every US city in terms of (0,15)-minute public transit accessibility. Several European cities have substantially larger zones than even the most public transit-oriented US city, New York City, which is the single US outlier in the $\mathcal{A}^P_{0,15}$ panel.

European and US cities are more similar in terms of their (45,60)-minute accessibility zones, but US comparative advantage remains in cars, and Europe’s in public transit. These patterns of comparative advantage are the result of offsetting factors that only come into play at farther distances from the CBD. The “patchiness” of public transit access makes covering large areas far away from the CBD difficult, and European rail-based transit becomes less efficient as we move to the outskirts of cities. At the same time, bus-based transit in the US, which leverages existing road infrastructure, helps make long-distance transit more comparable to that of European cities. Conversely, the relative disadvantage of cars in the dense urban cores of European cities becomes less of an issue in city outskirts.

FIGURE 3: ACCESSIBILITY ZONES ACROSS CITIES



Notes: Panel (A) shows a scatter plot of a metro area's population size against its (0,60)-minute accessibility-zone area for cars, separately for the US (red) and Europe (blue); it also shows linear fit lines and 95% confidence intervals for the Europe fit line. Panel (B) shows the replicates Panel (A) but instead shows (0,60)-minute public transit accessibility-zone areas. Panels (C)-(D) show histograms of the (0,15)-minute accessibility-zone areas for all cities in our samples for cars (left) and public transit (right), separately for the US and Europe. Panel (E)-(F) replicates Panels (C)-(D) show but for the (45,60)-minute accessibility-zone areas. All accessibility-zone areas in the figure are for commutes that arrive in the CBD at 8.45 am on a Wednesday.

TABLE 2: DRIVING VERSUS PUBLIC TRANSIT ACCESSIBILITY-ZONE AREAS

	US		Europe		Pooled	
Correlation	Value	Std. Error	Value	Std. Error	Value	Std. Error
$(\mathcal{A}^C_{0,15}, \mathcal{A}^P_{0,15})$	-0.041	0.273	-0.326	0.236	-0.219	0.181
$(\mathcal{A}^C_{15,30}, \mathcal{A}^P_{15,30})$	0.0659	0.124	-0.164	0.213	0.010	0.124
$(\mathcal{A}^C_{30,45}, \mathcal{A}^P_{30,45})$	0.464***	0.124	0.196	0.121	0.350***	0.109
$(\mathcal{A}^C_{45,60}, \mathcal{A}^P_{45,60})$	0.282	0.205	0.456***	0.094	0.408***	0.090

Notes: The table reports the coefficients from a regression of the log of the $(t, t+\Delta)$-minute driving accessibility-zone area on the log of the $(t, t+\Delta)$-minute public transit accessibility-zone area, run separately for $t = 0, 15, 30, 45$, $\Delta = 15$, and various samples. The "US" panel reports these coefficient estimates for a regression run with 52 US cities; the "Europe" panel reports the same coefficients for regressions run in our European sample of cities. The "Pooled" panel reports coefficients from running the regression in the pooled Europe and US samples controlling for a Europe fixed effect. All regressions control for log metro population from OECD data and include a constant. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

3.4 Are Driving and Transit Infrastructure Substitutes?

Do the evident US specialization in cars and European specialization in public transit imply car- and transit-based development strategies are substitutes? Table 2 shows how the sizes of the driving and transit accessibility-zone areas co-vary in the cross-section of cities, within regions, and in the pooled sample. The table presents conditional correlations between accessibility-zone areas for cars and transit, controlling for the population size of a city and a Europe fixed effect in the pooled specification.

Table 2 suggests a trade-off may exist between transit orientation and car orientation at short time distances close to city centers ($\mathcal{A}^C_{0,15}$ and $\mathcal{A}^P_{0,15}$). On average, cities with larger (0,15)-minute car accessibility zones have smaller public transit zones. In and around the city centers, transit and car infrastructure act like substitutes.

At longer distances, the sizes of car and transit accessibility zones correlate positively. This complementarity is probably due to the widespread use of public buses as public transit, especially in US cities. Better road infrastructure for cars also aids bus-based mobility.

Accessibility, Infrastructure, and Mode Choices. Appendix B explores how the accessibility-zone areas correlate with direct measures of road and public transit infrastructure and commuter mode choices.

The variable "miles of rail lines" is significantly positively correlated with $\mathcal{A}^P_{0,60}$ in both Europe and the US, but not with $\mathcal{A}^C_{0,60}$, as expected (Table B.1). Conversely, the length of the road network is more positively correlated with $\mathcal{A}^C_{0,60}$ than $\mathcal{A}^P_{0,60}$. Accessibility-zone areas are therefore likely to respond to commuting infrastructure investments.

Table B.2 shows commuter mode choices are correlated with the size of the accessibility area for that mode in the cross-section of cities. Car accessibility-zone areas are associated with increases in the share of commuters who drive and decreases in the share walking or biking to work. Transit accessibility zones $\mathcal{A}^P_{0,60}$ are associated with a reduction in the share of commuters driving and increases in both public transit users and walkers/bikers. Commuters will likely react to any future changes in the accessibility zones through their mode choices, which highlights the appropriate use (and limits) of our measures for policy analysis.

3.5 Partial-Equilibrium Effects of Increasing Accessibility

US cities lag behind their European counterparts in public transit accessibility. Equation 3 highlights two strategies US policymakers could pursue to address the low accessibility via public transit: change the size of accessibility zones or change the population density within existing zones. These two categories of changes correspond to distinct policy actions. Investments in the quality of public transit would increase public transit accessibility areas $\mathcal{A}^P_{t,t+\Delta}$, whereas investments in roads would increase car accessibility areas $\mathcal{A}^C_{t,t+\Delta}$. Investments in housing and the relaxing of zoning restrictions are likely to increase the density of commuters within accessibility zones, $\omega^m_{t,t+\Delta}$.

We use our model to conduct partial-equilibrium counterfactuals to study the effects of such policies on overall commuting efficiency, $\hat{\Theta}_{j^\star}$. We consider two policy interventions, first increasing the size of a particular accessibility zones by 10%, second increasing the population density within a given accessibility zone by 10%. Our outcome of interest is the overall CBD labor supply. We denote variables before the intervention as x and variables after the intervention as x'. We also define $\hat{x} = x'/x$, the factor of change in a given variable before and after the intervention. We can use equation 4 to express changes in commuting efficiency as a function of changes in accessibility and population density as follows:

$$(5) \qquad \hat{\Theta}_{j^*} = \sum_{t,m} \hat{\mathcal{A}}^m_{t,t+\Delta} \hat{\omega}^m_{t,t+\Delta} \psi^m_{t,t+\Delta} \quad \text{s.t.} \quad \psi^m_{t,t+\Delta} = \frac{\mathcal{A}^m_{t,t+\Delta} \omega^m_{t,t+\Delta} (1 - \bar{\tau}^m_{t,t+\Delta})}{\Theta_{j^*}},$$

where $\psi^m_{t,t+\Delta}$ is the initial contribution of mode m commutes from accessibility zone $(t, t+\Delta)$ to overall CBD labor supply.

To conduct our counterfactuals, we then have to construct the accessibility-zone weights, $\psi^m_{t,t+\Delta}$. Although we already discussed how to construct the accessibility zones, the population-density terms, $\omega^m_{t,t+\Delta}$, require extra work. We use data from the Longitudinal Employer-Household Dynamics (LEHD) program of the US Census to compute the number of residents in each accessibility zone that commute into the CBD using a particular mode. We divide these headcounts by the corresponding accessibility-zone area to obtain $\omega^m_{t,t+\Delta}$ for all US cities in our sample.[8] Table C.5 in the Appendix presents the overall commuting efficiency, Θ_{j^*}, as well as the mode-specific commuting efficiencies, $\Theta^P_{j^*}$ and $\Theta^C_{j^*}$, for all US cities in our sample.

Our first counterfactual is an increase in the accessibility-zone areas. We set $\hat{\mathcal{A}}^C_{0,15} = \hat{\mathcal{A}}^P_{0,15} = 1.1$ in equation 5. When increasing the accessibility-zone area, we recompute the population density in that zone. For example, an extension of $\mathcal{A}^C_{0,15}$ necessarily incorporates territory previously in $\mathcal{A}^C_{15,30}$, so we adjust $\omega^C_{0,15}$ to be an area-weighted average of the prior densities in $\mathcal{A}^C_{0,15}$ and $\mathcal{A}^C_{15,30}$. As a result, $\hat{\omega}^C_{0,15} \neq 0$ in our accessibility-zone enlargement counterfactuals.

Our second counterfactual increases the population density within various accessibility-zone areas. We set $\hat{\omega}^P_{t,t+\Delta} = 1.1$ in equation 5 while holding fixed the size of accessibility zones so that $\hat{\mathcal{A}}^m_{t,t+\Delta} = 1 \, \forall \, m, t$ and the density in all other accessibility zones. The underlying assumption is that areas closer to the center draw additional workers from outside of the $(0, 60)$-minute accessibility zone, that is, workers previously captured by the ξ residual, so that population density in other areas within the $(0, 60)$-minute zone are unaffected. If densification of the (0,15)-minute accessibility zone occurs instead by pulling in people from, for example, the (45,60)-minute zone, such reallocation would reduce the positive impact of densification on increasing CBD labor supply, $\hat{\Theta}_{j^*}$.

Table C.6 in the Appendix shows the increase in commuting efficiency from both policies for every city in our sample. Table 3 summarizes the effects within

[8] Unfortunately, LEHD-type commuting data are unavailable for European cities.

TABLE 3: COUNTERFACTUAL POLICIES TO ENHANCE COMMUTING EFFICIENCY

	$100\times(\hat{\Theta}_{j^*}-1)$							
	$\hat{\mathcal{A}}^m_{t,t+\Delta}=1.1, \hat{\omega}^m_{t,t+\Delta}<1$				$\hat{\omega}^m_{t,t+\Delta}=1.1$			
m	C,P	P	C,P	P	C,P	C,P	C,P	C,P
$(t,t+\Delta)$	(0,15)	(0,15)	(30,45)	(30,45)	(0,15)	(15,30)	(30,45)	(45,60)
Largest Cities	.023	.004	.025	.015	1.776	4.361	2.607	1.257
to	.022	.001	.020	.00	1.739	4.755	2.554	.952
↓	.028	.001	.013	.004	2.209	5.079	2.057	.656
Smallest	.031	.000	.014	.003	2.681	4.749	1.849	.721
Cities	.030	.001	.011	.002	3.557	4.28	1.575	.588
Average	.027	.001	.017	.006	2.411	4.646	2.116	.826

Notes: This table shows the average effect increase in the commuting access term across cities, Θ, resulting from a 10% increase in commuter density, $\omega^m_{t,t+\Delta}$, or accessibility-zone area, $\mathcal{A}^m_{t,t+\Delta}$ from their baseline, separately for five city-size quintiles. Quintile 1 contains the 20% of cities in our sample that are the largest in terms of OECD metro-area population numbers, Quintile 2 contains the 20% largest cities in the remaining sample, and so forth. Columns 6-9 show the percentage increase in commuting efficiency (Θ) that results from increasing the population density in the (0,15)-, (15,30)-, (30,45)-, and (45,60)-minute accessibility zones by 10% relative to their baseline value in the data for all modes of transport. Columns 2-5 show the percentage increase in commuting efficiency (Θ) that results from increasing the (0,15)- and (30,45)-minute accessibility-zone areas by 10% relative to their baseline value in the data. Columns 2 and 4 show the results from increasing the areas for both modes, Columns 3 and 5 from just increasing the public transit area.

quintiles of cities ordered by size. Quintile 1 contains the largest cities, for example, New York City; Quintile 2, the next group, for example, Phoenix, and so on. These exercises generate several insights.

First, any housing- and zoning-policy changes that densify cities (i.e., increase $\omega^P_{t,t+\Delta}$ by 10%) would increase commuting efficiency $\hat{\Theta}_{j^*}$ by considerably more than increasing $\mathcal{A}^P_{t,t+\Delta}$ by 10% and adjusting $\omega^P_{t,t+\Delta}$ accordingly. The relative effectiveness of such policies was not necessarily apparent ex ante, but the mathematical intuition is clear. Expanding infrastructure to enlarge $\mathcal{A}^P_{t,t+\Delta}$ expands the boundary of a given accessibility zone radially – away from the CBD into less dense areas – which produces smaller marginal gains, because fewer commuters are out there, so that the associated density decreases $\hat{\omega}^m_{t,t+\Delta}<0$. Furthermore, workers who switch from $\mathcal{A}^P_{15,30}$ to $\mathcal{A}^P_{0,15}$ only experience marginal time savings, because they were already living relatively close to the CBD. This prediction might change in a general equilibrium if workers from the city outskirts move into the enlarged accessibility zone in response to the improved transit conditions so that $\hat{\omega}^m_{t,t+\Delta}>0$. Such relocation forces would enhance the total benefits of increasing $\mathcal{A}^P_{t,t+\Delta}$. However, even then, those additional general-equilibrium benefits are only realized if the city makes complementary investments in housing in the areas better served by transit to allow those new workers to take advantage by relocating to areas that allow for shorter commutes.

Second, increasing car accessibility zones ($\mathcal{A}^C_{t,t+\Delta}$) in US cities is more effective in increasing aggregate commuting efficiency Θ_{j^*} than increasing transit accessibility areas ($\mathcal{A}^P_{t,t+\Delta}$). The reason is that car users dominate most US cities. In terms of equation 5, $\psi^C_{t,t+\Delta} > \psi^P_{t,t+\Delta} \forall t$ in almost all cities and almost all time distances. As a result, changes in public transit accessibility areas have lower weights, $\psi^m_{t,t+\Delta}$, attached to them and lead to only a minor increase in CBD accessibility. If pre-existing mode preferences are immutable, the straightforward implication is that US cities should focus on improving road infrastructure to maximize city productivity. However, this insight may again be attenuated in a general equilibrium if workers' mode choices respond endogenously to infrastructure improvements.

Third, the effect of raising public transit accessibility is larger in big cities than in small cities because significant differences exist in public transit ridership across those two groups. In terms of equation 5, the weights $\psi^P_{t,t+\Delta} \forall t$ are larger in bigger cities than in smaller ones, because in big cities, public transit commuting accounts for a larger fraction of commutes into the CBD.

Fourth, the effects of densification differ widely across accessibility-zone areas. Densifying the (15,30)-minute accessibility zone ($\omega^m_{15,30}$) produces the largest gains in Θ_{j^*}. Increasing the (0,15)-minute accessibility zone is less effective due to its small size, which means it contributes few workers to the CBD, that is, $\psi^m_{15,30} > \psi^m_{0,15}$. Increasing density in the (45,60)-minute zone is less effective because fewer residents commute into the CBD from there, that is, $\psi^m_{15,30} > \psi^m_{45,60}$. This result may again get attenuated in general equilibrium if removing zoning restrictions to build vertically in the areas surrounding a CBD in response to citizen and firm demand becomes easier. In other words, the political economy is also not immutable in a general equilibrium.

Fifth, the effects of densification differ widely across cities of different sizes. Densifying the (45,60)-minute zone is more effective in large cities such as New York than in smaller cities such as Raleigh, because they contributed more to total CBD labor supply ($\psi^m_{45,60}$ is much larger in New York than Raleigh). This finding reflects that large cities attract workers from far away, whereas CBDs of small cities mainly serve workers living close by. Conversely, densifying the (0,15)-minute zone is more effective for smaller towns than larger cities.

4. THE EXTERNALITY COST OF AMERICAN CITIES' CAR ORIENTATION

The question of whether to prioritize car or public transit infrastructure investments to increase CBD accessibility also has to consider that these approaches are likely associated with very different amenities and environmental and public health externalities. The transportation-policy literature has highlighted several different categories of externalities commonly associated with commuting systems (see Appendix Figure C.1 in Khreis et al., 2017), including congestion, land use, health, and pollution. We use these categories to organize our discussion of the externalities associated with car versus public transit accessibility.

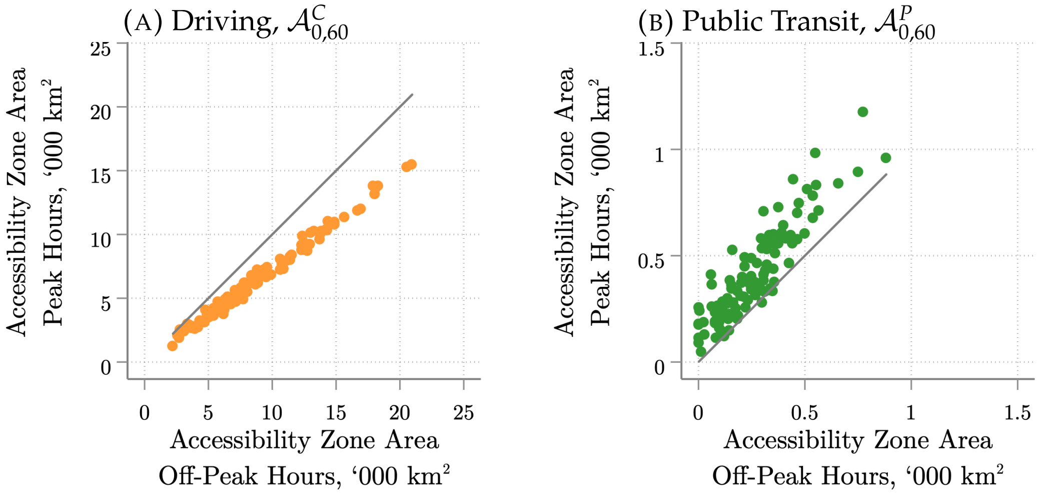
4.1 Congestion Externalities

Our theoretical framework did not explicitly model the dependence of commuting costs on the number of commuters using a given mode-route combination. In reality, commuting costs are often affected by the number of commuters using a particular route-mode combination. In terms of our model, this finding suggests $\tau_{i,j}^m = \tilde{\tau}_{i,j}^m(\bar{L}\phi_{i,j}^m)^{\xi^m}$, where $\xi^m > 0$ indicates usage slows down travel. When commuting costs are a function of the intensity of use, the size of an accessibility zone depends on the time of the day.

We use our accessibility measure to construct a straightforward test for the direction of such usage externalities. We re-compute our (0,60)-minute accessibility zones for each mode ($\mathcal{A}_{0,60}^m$) for commutes to the CBD that arrive on Sunday at 11 PM ("Off-peak Hours"). At that time, traffic on routes into the CBD, $\phi_{i,j^\star}^m$, should be much lower than on Wednesday at 8:45 AM ("Peak Hours") when we computed the accessibility zone areas thus far in the paper. The change in $\mathcal{A}_{0,60}^m$ between peak and off-peak hours gives us a sense of the direction and size of congestion on each mode.

The left panel of Figure 4 graphs peak-hour car accessibility-zone areas against off-peak areas. Each point represents a city in our sample. All points fall below the 45-degree line, which implies the size of the 60-minute area reachable

FIGURE 4: HOW ACCESSIBILITY-ZONE AREAS CHANGE WITH USAGE



Notes: This figure shows a scatter plot of cities' accessibility-zone areas during peak (Wednesday 8 AM) and off-peak (Sunday 11 PM) hours. The left panel is for car-based commutes, and the right is for public-transit-based commutes. Both panels also include a 45-degree line for reference.

from the CBD within 60 minutes expands during off-peak hours (i.e., a negative congestion externality, $\xi^C > 0$). About 27% of the land area that falls within 60 minutes of the CBD during off-peak hours is no longer accessible within 60 minutes during rush hour in the average city.

The right panel of Figure 4 conducts the same exercise for public transit accessibility zones with opposite results: on average, public transit accessibility is 56% *larger* during peak than off-peak hours ($\xi_P < 0$). These findings likely reflect the economies of scale in public transit provision. Because of the shared nature of travel, running buses and trains more frequently becomes profitable when more people use the system simultaneously.

The different sign of the usage externalities of the car- versus transit-based commuting systems complicates the policy advice on improving a city's commuting access $\hat{\Theta}_{j^*}$. Building more roads could slow car commutes if it induced mode-switching and increased congestion. On the other hand, building better public transit could improve the overall performance of the transit system via increased train frequency and station density, generating additional commuting-access gains via general-equilibrium forces.

4.2 Correlations with Land Use, Health, and Pollution

Next, we report a set of conditional correlations by regressing land use, health, and pollution outcomes on $\mathcal{A}^C_{0,60}$ and $\mathcal{A}^P_{0,60}$, controlling for other observable determinants of those outcomes as suggested by the relevant literature. We restrict our analysis to the US cities in our sample, due to a lack of consistent data for European cities.

Methodology. Because the land use, health, and pollution outcomes are available at the county level, we employ a two-step procedure to make the most use of the available county-level variation and maximize the statistical power of our analysis. In the first step, we run county-level regressions of each outcome (e.g., road density or PM2.5 pollution) on a set of control variables, such as a county's average socioeconomic, demographic, and geographic characteristics and its manufacturing orientation. We aggregate the residuals of that regression up to the city level in a second step and regress those residuals on our city-level measures of $\mathcal{A}^C_{0,60}$ and $\mathcal{A}^P_{0,60}$, along with a control for city population size. Our two-step procedure allows us to report the correlations that condition on the more-disaggregated county-level determinants of each outcome variable.

Land Use. Supporting car- versus public transit-based commutes requires different types of physical infrastructure. Their relative importance in a city's transportation policy likely affects urban land-use decisions. We explore this possibility in the top panel of Table 4.[9] The second-step associations between (the unexplained variation in) land-use outcomes and $\mathcal{A}^C_{0,60}$, $\mathcal{A}^P_{0,60}$ indicate cities with larger car accessibility zones have significantly more space allocated to streets and motorways per square kilometer of city land. Given car accessibility, public transit accessibility and road density do not exhibit a significant association. The correlation of the size of transit accessibility zones with bike-lane density is positive, but not statistically significant.

Next, we see the road density that improves car accessibility takes land away from other uses. A 10% increase in the car accessibility area ($\mathcal{A}^C_{0,60}$) is associated with a 1.4-percentage-point decrease in the share of green space. Green space only accounts for about 9% of the total land area of the average US city in our sample, making this effect sizable. A 10% increase in the car accessibility area

[9] Controls in the first stage of our land-use regressions: the fraction of owner-occupied housing, log population density, log income per capita, the share of black and Hispanic residents, mean democratic vote share, log mean temperature in January, the agricultural+mining share of employment.

Table 4: The Costs of Accessibility

Panel A: Land Use

	Log Total km per km^2			Green-space	Walking
	Motorway	Streets	Bike Lanes	per km^2	Index
$\log \mathcal{A}^P_{0,60}$	0.0107	-0.117	0.682	-0.00566	0.568
	(0.166)	(0.0982)	(0.748)	(0.0345)	(0.375)
$\log \mathcal{A}^C_{0,60}$	0.440***	0.291***	-0.0356	-0.139***	-0.864***
	(0.114)	(0.107)	(0.462)	(0.0424)	(0.281)
R^2	0.239	0.232	0.195	0.340	0.138

Panel B: Direct Health Externalities

	Share Physically	Sh. Poor + Far from	Share	Deaths per 1000	
	Inactive	Groceries	Obese	Traffic	Obesity
$\log \mathcal{A}^P_{0,60}$	-0.0195**	-0.00473	-0.00940	-0.189	-0.111
	(0.00763)	(0.00684)	(0.00626)	(0.220)	(0.219)
$\log \mathcal{A}^C_{0,60}$	0.0118*	0.0269***	0.0290***	0.0356	0.424**
	(0.00651)	(0.00801)	(0.00591)	(0.130)	(0.160)
R^2	0.144	0.276	0.376	0.020	0.131

Panel C: Pollution Externalities

	tC/km2/yr			log Mean	Aug. Temp
	$\log CO_2$	$\log NOx$	$\log PM2.5$	Noise	p90/p10
$\log \mathcal{A}^P_{0,60}$	0.0112	-0.146	-0.0636	0.00360	0.00441
	(0.101)	(0.135)	(0.170)	(0.00461)	(0.0322)
$\log \mathcal{A}^C_{0,60}$	0.334***	0.384***	0.331**	9.21e-05	-0.0510
	(0.0702)	(0.108)	(0.124)	(0.00309)	(0.0312)
R^2	0.311	0.230	0.127	0.021	0.040

Panel D: Indirect Health Externalities

	Deaths per 1000			Premature	log Life
	Asthma	COPD	Total	Deaths/100k	Expectancy
$\log \mathcal{A}^P_{0,60}$	0.0124	-0.205	5.672	0.0349	-0.00621
	(0.0517)	(0.674)	(4.050)	(0.0357)	(0.00435)
$\log \mathcal{A}^C_{0,60}$	0.123**	2.030***	6.682*	0.0962**	-0.0115**
	(0.0568)	(0.588)	(3.776)	(0.0389)	(0.00449)
R^2	0.188	0.232	0.195	0.277	0.324

Notes: All regressions control for city population in the second stage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. We add 1e-6 to the bike lanes to avoid zeros. All regressions are run on our sample of the 52 largest US cities. We present a complete list of data sources in Table C.1 in the Appendix; Table C.2 presents summary statistics including mean and median for every outcome variable.

is also associated with an 0.09-point decrease in the city's 20-point "walkability index."[10] By contrast, a 10% increase in the public transit accessibility area is associated with an 0.6-point *improvement* in the city's walkability index, but this estimate is not statistically significant.

Health. Panel B of Table 4 examines some health outcomes commonly associated with car usage.[11] A 10% increase in $\mathcal{A}^C_{0,60}$ is associated with a 0.12-percentage-point increase in the share of the population that is physically inactive. By contrast, a 10% increase in the public transit accessibility zone $\mathcal{A}^P_{0,60}$ has the opposite association: a 0.2-percentage-point *decrease* in the physically inactive share. Likewise, a 10% increase in car accessibility is associated with a 0.27-percentage-point increase in the share of the population in the city that is both poor and lacks easy access to groceries.[12] In other words, car accessibility is a positive predictor of "food deserts" (Allcott et al., 2019). Car accessibility is also associated with a larger share of the population that is obese.

Next, we use administrative cause-of-death data from the US Center for Disease Control and find a positive correlation between traffic deaths and $\mathcal{A}^C_{0,60}$, as well as a large negative correlation between traffic deaths and $\mathcal{A}^T_{0,60}$, but these correlations are not statistically significant. Obesity deaths, however, are statistically larger when cities are designed for CBDs to be more car accessible.

Pollution. Panel C shows car accessibility displays a strong positive association with air pollutants commonly associated with the burning of fossil fuels, CO_2, NOx, and $PM2.5$, with elasticities of 0.33-0.38; transit accessibility does not.[13] The public transit accessibility-zone area, $\mathcal{A}^P_{0,60}$, generally has a negative (but insignificant) coefficient in these pollution regressions. No correlation exists between car accessibility and noise pollution emitted by transportation sources or heat islands.

Mortality. Increased pollution, physical inactivity, obesity, and food deserts may affect downstream health outcomes such as mortality and life expectancy. Our regressions provide suggestive evidence of such effects. More car-accessible

[10]The EPA's National Walkability Index is a composite score of Census block groups' relative amenability to pedestrian trips on a 1-20 scale and accounts for street-intersection density, proximity to transit stops, and land-use diversity.

[11]First-stage controls: the shares of black residents, Hispanic residents, residents above age 65, residents with heavy drinking habits, smokers, and log population density.

[12]"Poor" are residents with incomes below twice the poverty line. "Lack of easy access" refers to living more than one mile from the nearest grocery store.

[13]First-stage controls are log income per capita, log population density, the urban share of the population, the share of employment in manufacturing (CBP), and log county centroid latitude.

cities have higher deaths from asthma, chronic pulmonary diseases (COPD), and a higher total and premature death rate, holding constant the county-level demographic variables that predict these outcomes. A 10% increase in $\mathcal{A}^{C}_{0,60}$ is associated with a 0.12% decrease in life expectancy among residents (elasticity of 0.01). Transit accessibility-zone areas do not significantly correlate with any mortality outcome.

In summary, greater car accessibility is associated with larger negative externalities in pollution, health, and land use within the sample of US cities. These insights are generally consistent with prior literature that has studied the effects of transportation on land use (Glaeser and Kahn, 2010; Duranton and Puga, 2015), pollution (Parry et al., 2007; Gendron-Carrier et al., 2022; Schlenker and Walker, 2016), and health (Knittel et al., 2016; Currie and Walker, 2011). Adler and van Ommeren (2016) study trade-offs between modes and find consistent results. Khreis et al. (2017) provide an excellent summary of the public health literature on how urban transport policy and planning affect the built environment, transport-infrastructure provision, mode choices, and health outcomes.

5. CONCLUSION

Our research highlights a fundamental trade-off in the design of commuter systems. Cars are generally more effective at providing city-center access to far larger surrounding land areas (and therefore, a larger potential population) than public transit in both the US and Europe. But car-based commuting imposes larger negative externalities and health costs on society. When cities are designed to provide greater car accessibility to CBDs, this type of access appears to be associated with lifestyle choices that produce worse health, environmental, and land-use outcomes than public transit access would. Because car-accessible cities are more polluted and less walkable, and residents are more physically inactive, obese, and unhealthy, these residents experience greater mortality rates and lower life expectancy. By contrast, transit accessibility is not associated with these negative externalities.

The current car orientation of the US is a result of policy choices after World War II to invest heavily in roads and highways. That highway infrastructure – designed to last 50-70 years – is now approaching their expiration dates (New York Times, Feb. 11, 2022), and cities need to consider alternative policy directions.[14] Many cities, such as Syracuse and Detroit, have committed to replacing stretches of the interstate with more connected, walkable neighborhoods.[15] Other cities, such as Houston, are expanding their highway systems in an attempt to make CBDs more accessible (Los Angeles Times, November 11, 2021).

The transportation infrastructure investments now made will determine the future orientation of US transportation infrastructure and affect how US residents live, work, and commute over the next 50 years. As a result, city planners need to consider not only the productivity and efficiency effects of focusing on roads versus public transit infrastructure, but also the social, environmental, congestion, and health consequences of their choices. The CBD accessibility measures we propose are easy for policymakers to compute for any city, for time of day, or even repeatedly over time, and can aid such policy evaluations.

Study Limitations and Directions for Future Work. Our study is descriptive by design, and our goal was to construct theory-consistent measures of CBD accessibility to aid policy analysis. The partial-equilibrium results we report in section 3.5 should not be read as "predictive," because they might change as people and firms adjust their mode choices, workplace, and residential location choices, or as politicians respond to citizen demands and alter zoning restrictions. To properly account for those general-equilibrium changes, the measures we have developed will need to be paired with theoretical frameworks where mode and location choices adjust, and the negative externalities stemming from those choices are accounted for. Existing quantitative spatial models of commuting could serve as a natural point of departure for developing such holistic frameworks (e.g., Allen et al., 2015; Ahlfeldt et al., 2015; Monte et al., 2018).[16]

Similarly, the associations between car and transit accessibility zones and various health and pollution outcomes we report in section 4 are correlations, not causal effects of commuting-infrastructure changes. Policy shocks, natural experiments, or historical or geographic instruments that extract exogenous components of the variation in accessibility zones are necessary to make

[14]The Biden administration's infrastructure plan reflects some potential changes in the focus of transportation policy; see (Los Angeles Times, November 11, 2021).

[15]New Orleans and Dallas face pressure from residents and activists to address the pollution, noise, and safety hazards associated with its mega-roads (New York Times, May 27, 2021).

[16]Applications include an evaluation of the Los Angeles Metro Rail extension (Severen, 2022), measuring the effects of the world's largest bus rapid transit system in Bogotá (Tsivanidis, 2022), and optimal-transit-system design in general equilibrium frameworks (Fajgelbaum and Schaal, 2020; Allen and Arkolakis, 2022). Redding and Rossi-Hansberg (2017) provide a general summary of this literature.

causal statements. Although many studies estimate the causal effects of a particular type of transportation infrastructure on a specific health outcome (e.g., Gendron-Carrier et al., 2022; Currie and Walker, 2011), no study has attempted a comprehensive assessment of the wide range of costs and benefits of transport-infrastructure interventions. The marginal value of public funds approach (Hendren and Sprung-Keyser, 2020) provides an exciting framework to combine different causal estimates and map them into a dollar-denominated cost-benefit analysis.

Lastly, our approach does not account for the monetary costs of alternative mode choices -for example, the costs of parking in the CBD, car maintenance, insurance, or the cost of tickets for public transit. Such costs are significant drivers of mode choices and are also natural policy levers to design car- or transit-oriented commuting systems.

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Online Appendix

A. Alternative Measurement Approaches

Different approaches can be taken to construct accessibility zones in the data. In the body of the paper, we rely on proprietary software by a company called "Traveltime, Inc" (https://app.traveltime.com/), which automates the construction process. Other companies offer the same service, and constructing accessibility zones from first principles is possible using any route-finding API.

Table A.1: Pairwise Correlations among Accessibility-Zone Areas

Source	Traveltime	Targomo	Google Maps
Traveltime	1.00	-	-
Targomo	0.76	1.00	-
Google Maps	0.85	0.74	1.00

Notes: The table compares the (0,60)-minute car accessibility-zone areas computed using three different approaches. All accessibility-zone areas are for commutes that arrive in the CBD at 8:45 AM on a Wednesday. The different computing approaches are: using the proprietary software of TravelTime Inc (row 1) or Targomo (row 2) and using Python and the GoogleMaps API to construct the zones ourselves (row 3).

Table A.1 shows the correlations between the (0,60)-minute car accessibility-zone areas from "Traveltime, Inc" and the same areas computed using an alternative software provider, Targomo (https://www.targomo.com), and an approach that uses Python combined with optimal routes obtained from Google Maps. The correlations are high: all three sources deliver comparable estimates of the accessibility-zone areas.

B. Accessibility, Infrastructure, and Mode Choices

In this section, we examine the correlations between our accessibility-zone areas and traditional measures of infrastructure (e.g., road length), and mode choices of commuters.

Accessibility and Infrastructure. Table B.1 shows coefficient estimates from a regression of (0,60)-minute accessibility-zone areas in the US and Europe on traditional measures of transportation infrastructure, separately for public transit and cars. We include a constant and a control for city population size in all regressions. The pooled regression also includes a Europe dummy.

As expected, the public transit accessibility-zone area and the number of rail miles positively correlate in the US and Europe. Similarly, car accessibility and total street miles are strongly positively correlated in the US. The same correlation is less strong and insignificant in Europe, perhaps reflecting that large street networks in old European city centers were not designed for cars. Road length in the US also correlates positively with the size of public transit accessibility zones, perhaps because US transit systems in many cities rely on buses. European public transit systems rely much more on trams, subways, and railroads.

TABLE B.1: ACCESSIBILITY ZONES AND INFRASTRUCTURE

	United States		Europe		Pooled	
log of...	$\mathcal{A}^P_{0,60}$	$\mathcal{A}^C_{0,60}$	$\mathcal{A}^P_{0,60}$	$\mathcal{A}^C_{0,60}$	$\mathcal{A}^P_{0,60}$	$\mathcal{A}^C_{0,60}$
Rail Miles	0.0656**	-0.0460	0.191***	0.0929*	0.122***	0.0312
	(0.0292)	(0.0470)	(0.0666)	(0.0497)	(0.0283)	(0.0343)
Street Miles	0.797**	0.992***	0.0681	0.268	0.473*	0.615**
	(0.307)	(0.268)	(0.326)	(0.344)	(0.255)	(0.244)
Observations	52	52	51	51	103	103
R-squared	0.658	0.237	0.334	0.200	0.582	0.268

Notes: All regressions regress log accessibility-zone areas on log measures of transportation infrastructure. All regressions include a constant term and a control for population, which we do not report. The pooled regressions include a Europe dummy which we do not report. We add a 1 to the total rail miles in cities with a rail mile count of 0. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. We present a complete list of data sources in Table C.1.

Accessibility and Transportation-Mode Choice. Table B.2 regresses mode shares for driving, public transit, and non-motorized commutes on our accessibility measures. The mode shares are the fraction of workers commuting into the CBD using a particular mode. As expected, in cities with larger driving accessibility zones, more people use the car to get to work, and fewer people use public transit. Likewise, in cities with larger public transit accessibility zones, more people use public transit for their commute, and fewer people use cars.

Interestingly, public transit accessibility areas are also positively correlated with the walk/bike mode share. By contrast, larger car accessibility areas negatively correlate with the use of these modes, even after holding fixed the population size of the city. These differences in correlations suggest cities that have more public transit and fewer cars are more walkable, which helps explain some of the externality costs of car orientation we observe in section 4.

The Europe fixed effect indicates European workers are substantially less likely to use cars than are US workers, and lower driving propensity is equally split between the increased likelihood of taking public transit, and walking/biking to work. Workers in large cities are more likely to use public transit and less likely to drive.

TABLE B.2: ACCESSIBILITY ZONES AND MODE SHARES

	Share of CBD Commutes via		
	Driving	Transit	Walk+Bike
$\log \mathcal{A}^{P}_{0,60}$	-0.157***	0.118***	0.0326**
	(0.0306)	(0.0311)	(0.0163)
$\log \mathcal{A}^{C}_{0,60}$	0.0993***	-0.0438	-0.0517**
	(0.0278)	(0.0284)	(0.0246)
log Population	-0.0621*	0.0689**	-0.00417
	(0.0340)	(0.0339)	(0.0123)
Europe Dummy	-0.200***	0.101***	0.105***
	(0.0342)	(0.0293)	(0.0155)
Observations	96	96	98
R-squared	0.751	0.616	0.608

Notes: All regressions include a constant term, which we do not report. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. We present a complete list of data sources in Table C.1. Note the mode shares across Driving, Transit, and Walk+Bike do not sum to 1, due to the "Other" category in data.

C. Additional Figures and Tables

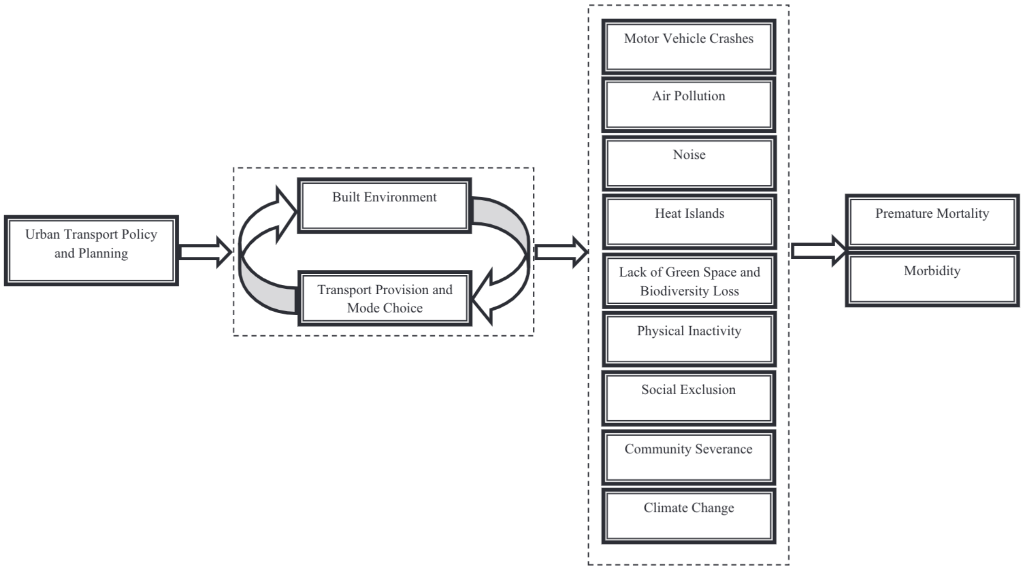
In this section, we present additional Figures and Tables.

Figure C.1 presents a graphic taken from Khreis et al. (2017), which diagrammatically shows the linkages between urban transport policy and planning, and adverse health impacts. The figure helped us focus on what variables to analyze in section 4 above.

Table C.1 provides the data source and unit of measurement of every variable used in the paper. Similarly, Table C.2 provides summary statistics of all the variables used throughout the paper. Tables C.3 and C.4 list the (0,15)-, (15,30)-, (30,45)-, and (45,60)-minute accessibility-zone areas for every US and European city in our sample, separately for driving and public transit. Table C.5 presents our estimates for CBD labor supply for every US city in our sample, overall and by mode.

Table C.6 presents the predicted changes in CBD labor supply, $\hat{\Theta}_{j^*}$, resulting from the partial-equilibrium counterfactual exercises in section 3.5, for each US city in our sample.

FIGURE C.1: OVERVIEW OF TRANSPORTATION POLICY EXTERNALITIES



Notes: This figure shows Figure 1 from Khreis et al. (2017), which in their paper was entitled ”Linkages between Urban Transport and Adverse Health Impacts.”

TABLE C.1: DATA SOURCES

Variable	Unit	Description	Source
Demographics and Economic			
Metro Area population	Count	Population of corresponding OECD metro area	OECD
Urban share of the population	Proportion	Share of population living in urban areas, 2010	NHGIS Table H7W (Census 2010)
Share of employment in manufacturing	Proportion	Share of employment in NAICS codes 31-33, 2015	County Business Patterns
65+-year-olds	Proportion	Share of population aged 65+	NHGIS Table H76 (Census 2010)
Owner-occupied fraction	Proportion	Share of occupied housing units owner-occupied, 2006-2010	NHGIS Table JRK (2006-2010 ACS)
Population Density	Persons per km^2	Population per square kilometer, 2010	NHGIS Table H7X (Census 2010)
Income per capita	$	Per capita income in the past 12 months, 2006-2010	NHGIS Table JQB (2006-2010 ACS)
Share of black residents	Proportion	Share of population Black or African American alone	NHGIS Table H7X (Census 2010)
Share of hispanic residents	Proportion	Share of population Hispanic or Latino	NHGIS Table H7Y (Census 2010)
Mean democratic vote share	Proportion	Mean vote share of democratic presidential candidates, 2000-2016	MIT Election Data + Science Lab
Agricultural share of employment	Proportion	Share of employment in NAICS code 11, 2015	County Business Patterns
Commuters by Mode from Tract to Tract			
Infrastructure and Land Use			
Total street length	kilometer	Used OpenStreetMap API to count total street length within each metro area	OpenStreetMap
Total motorway length	kilometer	Used OpenStreetMap API to count total motorway length within each metro area	OpenStreetMap
Total Bike Lanes length	kilometer	Used OpenStreetMap API to count total bike lane length within each metro area	OpenStreetMap
Greenspace area	Proportion	Share area covered by parks	OpenStreetMap
Pollution			
CO2	Tons	Total annual on-road CO2 emissions	EPA National Emissions Inventory (2017)
NOX	Tons	Total annual on-road NOX emissions	EPA National Emissions Inventory (2017)
PM 2.5	Tons	Total annual on-road PM 2.5 emissions	EPA National Emissions Inventory (2017)
Noise	Decibels	Noise energy emitted from transportation sources over a 24-hour period, averaged over receptor locations within grid cell	National Transportation Noise Mapping Tool
90th/10th percentile August temperature	Ratio	Ratio of 90th to 10th percentile grid-cell-level August temperature (2019)	MODIS Land Surface Temperature and Emissivity (MOD11)
Mean January temperature	Degrees Celsius	Mean grid-cell-level January temperature (2019)	MODIS Land Surface Temperature and Emissivity (MOD11)
Health			
Residents with heavy drinking habits	Proportion	Share of adults reporting binge or heavy drinking.	2020 County Health Rankings
Residents who are smokers smokers	Proportion	Share of adults who are current smokers.	2020 County Health Rankings
Walking Index	Index (1-20)	Composite index of street intersection density, proximity to transit stops, and diversity of land uses	EPA National Walkability Index
Share Physically Inactive	Proportion	Share of adults age 20 and over reporting no leisure-time physical activity	2020 County Health Rankings
Share poor and far from groceries	Proportion	Share of population with income $< 2\times$ poverty line and live $>$ 1 mi. from grocery store	2020 County Health Rankings
Share obese	Proportion	Share of (age 20+) population with BMI¿30 kg/m2	2020 County Health Rankings
Death			
Total Deaths	Deaths/1000 residents	All deaths	CDC Multiple Cause of Death 1999-2019
Traffic Deaths	Deaths/1000 residents	Transport accident deaths according to International Classification of Diseases	CDC Multiple Cause of Death 1999-2019
Obesity Deaths	Deaths/1000 residents	Obesity-caused deaths according to International Classification of Diseases	CDC Multiple Cause of Death 1999-2019
Asthma Deaths	Deaths/1000 residents	Asthma-caused deaths according to International Classification of Diseases	CDC Multiple Cause of Death 1999-2019
COPD Deaths	Deaths/1000 residents	Chronic obstructive pulmonary disease-caused deaths according to International Classification of Diseases	CDC Multiple Cause of Death 1999-2019
Premature Deaths	Years/100k population	Years of potential life lost before age 75 per 100,000 population	2020 County Health Rankings
Life Expectancy	Years	Average number of years a person can expect to live	2020 County Health Rankings

Notes: This table presents a description, the unit of measurement, and the source for every empirical variable used in the paper.

TABLE C.2: SUMMARY STATISTICS

Variable	Aggregation	Unit	Mean	Standard Deviation	Min	Max
Demographics and Economic						
(Total) Metro Area population	County	Persons	3016273	4335979	251446	19961045
Urban share of the population	County	Proportion	0.41	0.31	0	1
Share of employment in manufacturing	County	Proportion	0.15	0.12	0	0.75
65+-year-olds	County	Proportion	0.16	0.04	0.04	0.43
Owner-occupied fraction	County	Proportion	0.73	0.08	0.21	0.91
Population Density	County	Persons per km^2	98.66	661.70	0.05	26544.42
Income per capita	County	$	22452.07	5370.60	7772.00	64381.00
Share of black residents	County	Proportion	0.09	0.15	0.00	0.86
Share of hispanic residents	County	Proportion	0.08	0.13	0.00	0.96
Mean democratic vote share	County	Proportion	0.38	0.13	0.07	0.90
Agricultural share of employment	County	Proportion	0.01	0.02	0	0.35
Commuters by Mode from Tract to Tract						
Infrastructure and Land Use						
Total street length	County	kilometers	2611.85	2174.43	0.00	37046.48
Total motorway length	County	kilometers	85.75	159.39	0.00	2650.58
Total Bike Lanes length	County	kilometers	16.82	106.99	0.00	3734.72
Greenspace area	County	Proportion	0.09	0.17	0	1
Pollution						
CO2	County	Tons	465.38	1440.33	1.39	42337.96
NOX	County	Tons	0.84	1.91	0.01	45.55
PM 2.5	County	Tons	0.04	0.12	0.00	3.86
Noise	County	Decibels	53.57	1.63	45.32	56.96
90th/10th percentile August temperature	County	Ratio	1.13	0.14	1.00	2.17
Mean January temperature	County	Degrees Celsius	2.64	8.21	-20.42	23.19
Health						
Residents with heavy drinking habits	County	Proportion	0.17	0.03	0.08	0.29
Residents who are smokers smokers	County	Proportion	0.17	0.04	0.06	0.41
Walking Index	County	Index (1-20)	6.49	1.92	2.86	16.00
Share Physically Inactive	County	Proportion	0.27	0.06	0.10	0.50
Share poor and far from groceries	County	Proportion	0.09	0.08	0.00	0.72
Share obese	County	Proportion	0.33	0.05	0.12	0.58
Death						
COPD Deaths per 1000	County	Deaths/1000 residents	23.74	8.99	1.04	64.08
Total Deaths	County	Deaths/1000 residents	216.89	53.40	40.33	440.01
Traffic Deaths per 1000	County	Deaths/1000 residents	2.43	1.26	0.30	13.06
Obesity Deaths per 1000	County	Deaths/1000 residents	2.30	1.08	0.30	9.68
Asthma Deaths per 1000	County	Deaths/1000 residents	0.76	0.45	0.14	8.46
Premature Deaths	County	Years/100k population	8525.83	2765.87	2730.60	43939.07
Life Expectancy	County	Years	77.45	3.01	61.63	104.74

Notes: This table presents summary statistics and the spatial unit of measurement for every empirical variable used in the paper.

Table C.3: Accessibility Areas in the US

City	$\mathcal{A}^C_{0,15}$	$\mathcal{A}^C_{15,30}$	$\mathcal{A}^C_{30,45}$	$\mathcal{A}^C_{45,60}$	$\mathcal{A}^P_{0,15}$	$\mathcal{A}^P_{15,30}$	$\mathcal{A}^P_{30,45}$	$\mathcal{A}^P_{45,60}$
Albany, NY	97.31	792.1	1921	3885	2.875	20.62	69.74	86.03
Atlanta, GA	362.1	1716	3155	5743	3.949	45.47	175.1	380.9
Austin, TX	225.3	1507	3160	5852	3.046	25.49	71.23	99.79
Birmingham, AL	573.4	1840	3793	7541	3.265	20.13	39.89	46.08
Boston, MA	75.48	727.6	1796	3533	6.132	70.23	177.9	206.8
Buffalo, NY	150.2	794.6	1537	2583	5.538	38.22	100.9	115.2
Charlotte, NC	300.6	1320	2560	5127	6.948	53.32	135.0	165.8
Chicago, IL	286.0	1336	2452	4273	8.044	70.95	201.1	293.7
Cincinnati, OH	100.7	913.8	2407	4199	3.150	25.79	78.80	122.6
Cleveland, OH	107.3	738.2	1892	3419	5.458	39.63	106.3	184.8
Columbus, OH	173.5	1243	2832	6033	4.922	43.60	116.5	166.7
Dallas, TX	313.0	2388	4662	8069	2.645	29.87	125.9	206.0
Denver, CO	17.15	726.7	2066	4123	3.859	35.25	120.2	209.6
Detroit, MI	138.2	1021	2069	3515	3.048	17.62	59.85	142.5
Fresno, CA	456.2	1701	2861	5215	3.435	25.45	62.51	79.29
Hartford, CT	443.9	1582	2852	4956	6.019	60.12	160.9	182.1
Houston, TX	482.4	2532	4051	6673	2.365	32.51	164.2	308.2
Indianapolis, IN	151.8	1170	2856	6175	3.273	36.81	108.4	141.4
Jacksonville, FL	105.7	666.6	1140	2210	2.755	17.76	58.59	110.7
Kansas City, MO	223.7	1429	3296	7018	4.489	26.65	100.0	166.5
Las Vegas, NV	384.8	992.0	745.4	787.4	3.014	24.94	80.35	144.8
Los Angeles, CA	323.9	1800	2068	3018	6.576	63.89	205.7	448.4
Louisville, KY	210.0	1258	2811	5877	2.247	18.74	61.67	101.7
Memphis, TN	417.0	1822	3689	7186	4.606	24.28	54.25	91.47
Miami, FL	93.94	585.2	856.3	951.2	2.684	32.11	69.47	171.8
Milwaukee, WI	145.6	1054	2275	4565	2.491	24.55	98.15	150.2
Minneapolis, MN	185.0	1613	3121	6406	3.603	33.58	137.8	312.3
Nashville, TN	443.9	2168	4617	7997	2.716	21.29	80.02	78.58
New Haven, CT	86.40	693.9	1405	2559	5.289	43.38	76.31	93.87
New Orleans, LA	264.1	463.3	650.9	2334	3.239	12.95	54.20	87.31
New York, NY	56.05	936.0	2094	3489	6.540	46.79	168.8	372.7
Oklahoma City, OK	223.2	1448	3218	6956	2.045	23.18	98.39	116.4
Orlando, FL	127.4	869.8	1639	2247	3.266	22.67	75.42	139.1
Philadelphia, PA	206.5	1240	2721	4981	10.27	90.14	195.0	267.6
Phoenix, AZ	68.80	968.3	2108	3018	2.579	30.86	108.0	202.2
Pittsburgh, PA	230.4	1082	2305	5136	3.988	54.70	144.5	195.0
Portland, OR	34.60	608.0	1685	3262	3.393	42.69	131.7	188.5
Raleigh, NC	48.31	481.0	1497	3308	4.269	31.76	75.03	125.2
Richmond, VA	214.1	1184	2212	4578	2.879	31.08	52.89	32.51
Sacramento, CA	321.2	1398	3351	4987	3.539	27.56	86.59	138.3
Salt Lake City, UT	107.4	799.8	1085	2069	2.918	28.95	89.76	151.4
San Antonio, TX	460.8	2047	3788	7239	2.605	25.83	124.1	187.3
San Diego, CA	278.1	910.6	1134	1684	5.142	23.58	83.09	169.8
San Francisco, CA	58.01	522.3	1161	2454	7.943	50.79	113.6	186.7
Seattle, WA	98.44	687.5	1130	1972	5.003	40.87	147.6	260.5
St. Louis, MO	263.0	1604	2824	6222	3.564	39.14	91.38	171.5
St. Petersburg, FL	148.8	237.8	840.2	1978	3.270	27.64	46.64	49.18
Tampa, FL	140.2	685.4	1539	2442	2.152	12.87	45.37	84.29
Tucson, AZ	249.8	1107	1863	2582	3.110	23.54	109.0	119.5
Tulsa, OK	140.6	1375	2755	5937	2.265	4.047	35.25	47.17
Virginia Beach, VA	119.0	498.7	582.9	1431	1.730	2.993	9.180	30.76
Washington, DC	151.6	1031	2092	3937	4.359	37.82	156.9	356.4
Average	213.2	1160	2293	4303	4.010	33.74	102.7	167.1

Notes: The table presents the size of the area from which the CBD of a given city is accessible within (0,15)-, (15,30)-, (30,45)-, or (45,60)-minute commutes via either cars or public transit. The areas have been constructed for Wednesday at 8.30 AM. The areas are computed using the service of the "Traveltime, Inc." website.

TABLE C.4: ACCESSIBILITY AREAS IN EUROPE

City	$\mathcal{A}^C_{0,15}$	$\mathcal{A}^C_{15,30}$	$\mathcal{A}^C_{30,45}$	$\mathcal{A}^C_{45,60}$	$\mathcal{A}^P_{0,15}$	$\mathcal{A}^P_{15,30}$	$\mathcal{A}^P_{30,45}$	$\mathcal{A}^P_{45,60}$
Amsterdam, Netherlands	109.5	778.1	1803	3441	5.431	50.98	139.3	266.5
Athens, Greece	36.36	312.0	623.0	1084	9.151	70.86	136.7	109.8
Barcelona, Spain	7.603	56.38	449.3	1334	11.57	67.93	106.7	221.1
Berlin, Germany	42.26	181.7	572.2	1771	7.592	103.0	289.6	437.5
Birmingham, UK	62.61	737.0	1857	3745	4.233	51.51	174.2	219.7
Bordeaux, France	8.097	149.4	1044	2971	4.097	38.06	103.9	184.8
Bremen, Germany	66.20	628.3	2113	5103	6.046	50.65	133.9	209.9
Brussels, Belgium	22.74	367.5	1852	4953	7.949	100.3	253.5	619.9
Budapest, Hungary	30.35	311.9	1211	2933	4.193	45.23	147.7	231.6
Cologne, Germany	46.56	671.2	2674	6199	6.341	67.37	240.6	542.0
Copenhagen, Denmark	33.06	197.4	873.1	2466	12.89	83.71	218.8	323.7
Dortmund, Germany	22.77	587.0	2189	5842	7.560	59.76	150.7	363.0
Dresden, Germany	45.10	299.5	1473	3608	3.873	46.94	117.1	169.8
Dublin, Ireland	119.6	800.3	1722	3132	5.168	47.40	129.6	190.0
Duesseldorf, Germany	46.96	874.4	3092	6011	3.530	45.26	152.1	377.4
Frankfurt, Germany	38.91	580.7	2035	4625	12.55	92.92	255.6	450.2
Glasgow, UK	66.01	679.9	1524	2421	3.458	43.28	166.0	274.9
Hamburg, Germany	27.30	254.0	1080	3522	8.495	76.90	199.3	424.7
Hanover, Germany	67.38	632.6	1788	4149	14.90	94.09	175.6	307.8
Helsinki, Finland	10.52	112.6	620.3	1943	8.288	82.64	248.2	261.3
Katowice, Poland	90.61	742.0	1762	3594	2.355	36.09	144.0	254.5
Krakow, Poland	16.77	196.4	788.7	2086	6.432	55.38	123.3	189.5
Leeds, UK	56.87	543.7	1420	2980	4.380	31.48	100.5	246.0
Lille, France	8.409	355.6	2224	4785	3.203	44.16	117.6	178.1
Lisbon, Portugal	31.58	449.3	853.0	1415	6.335	51.80	81.74	108.2
Liverpool, UK	45.64	255.2	693.2	1724	3.957	40.57	120.1	145.5
London, UK	16.62	88.88	237.3	851.6	3.647	50.39	282.6	621.2
Lyon, France	5.122	309.0	1587	3694	6.150	56.80	163.4	221.4
Madrid, Spain	9.469	486.2	1491	3082	13.23	112.2	292.7	358.9
Manchester, UK	57.68	392.0	1180	2688	4.512	36.53	166.5	343.6
Marseille, France	17.37	271.6	975.6	1623	5.434	35.92	82.36	129.2
Milan, Italy	7.578	72.59	846.8	3164	8.680	79.60	146.5	293.0
Munich, Germany	48.12	626.8	2574	5918	5.254	89.25	284.9	448.8
Naples, Italy	157.8	838.8	1062	2017	4.382	16.51	27.60	60.83
Nuremberg, Germany	40.45	510.6	2429	4977	5.077	73.23	179.0	274.1
Oslo, Norway	40.54	363.8	1017	2301	7.999	80.11	203.4	264.4
Paris, France	4.561	66.13	539.6	1742	12.23	110.2	375.1	675.0
Porto, Portugal	72.08	629.2	1441	2323	6.883	45.20	75.31	73.31
Prague, Czech Republic	32.88	442.6	1717	4578	9.105	97.95	243.9	395.2
Rome, Italy	27.41	259.4	1102	2553	11.22	70.87	134.8	165.4
Rotterdam, Netherlands	87.62	767.3	1631	3437	6.953	57.96	194.9	318.4
Seville, Spain	29.95	402.8	1252	2016	2.585	17.84	46.85	80.02
Sheffield, UK	21.09	217.7	995.3	2241	2.814	21.58	79.77	114.4
Stockholm, Sweden	23.42	429.4	1159	2425	2.480	55.30	232.7	408.2
Stuttgart, Germany	38.40	568.5	1872	3576	9.213	84.14	218.7	392.1
Toulouse, France	5.698	194.8	1871	4642	7.603	68.97	178.8	270.1
Turin, Italy	29.41	368.8	1419	3156	4.836	35.61	93.16	174.8
Valencia, Spain	33.44	473.3	1318	1852	6.131	45.97	74.30	89.12
Vienna, Austria	14.61	221.7	947.2	2845	11.50	101.4	190.2	293.9
Warsaw, Poland	38.83	293.2	1165	3158	8.231	99.27	207.1	360.6
Zuerich, Switzerland	54.20	790.6	1685	3174	8.194	83.02	272.4	526.1
Average	40.67	428.2	1409	3174	6.829	62.83	170.1	287.4

Notes: The table presents the size of the area from which the CBD of a given city is accessible within (0,15)-, (15,30)-, (30,45)-, or (45,60)-minute commutes via either cars or public transit. The areas have been constructed for Wednesday at 8.30 AM. The areas are computed using the service of the "Traveltime, Inc." website.

TABLE C.5: CBD LABOR SUPPLY, Θ, ACROSS CITIES

City	Θ	Θ^C	Θ^P
Albany, NY	0.791	0.748	0.0429
Atlanta, GA	0.786	0.723	0.0635
Austin, TX	0.861	0.824	0.0371
Birmingham, AL	0.891	0.887	0.00400
Boston, MA	0.619	0.317	0.303
Buffalo, NY	0.873	0.790	0.0822
Charlotte, NC	0.818	0.788	0.0299
Chicago, IL	0.607	0.268	0.339
Cincinnati, OH	0.804	0.754	0.0499
Cleveland, OH	0.808	0.729	0.0794
Columbus, OH	0.853	0.823	0.0305
Dallas, TX	0.790	0.761	0.0290
Denver, CO	0.702	0.637	0.0651
Detroit, MI	0.830	0.806	0.0245
Fresno, CA	0.898	0.886	0.0118
Hartford, CT	0.835	0.781	0.0534
Houston, TX	0.793	0.768	0.0255
Indianapolis, IN	0.853	0.842	0.0106
Jacksonville, FL	0.762	0.756	0.00636
Kansas City, MO	0.848	0.820	0.0278
Las Vegas, NV	0.892	0.858	0.0342
Los Angeles, CA	0.766	0.687	0.0792
Louisville, KY	0.870	0.834	0.0368
Memphis, TN	0.891	0.875	0.0161
Miami, FL	0.833	0.798	0.0347
Milwaukee, WI	0.836	0.763	0.0722
Minneapolis, MN	0.696	0.575	0.120
Nashville, TN	0.865	0.851	0.0134
New Haven, CT	0.728	0.677	0.0516
New Orleans, LA	0.762	0.721	0.0410
New York, NY	0.609	0.124	0.485
Oklahoma City, OK	0.882	0.874	0.00809
Orlando, FL	0.805	0.792	0.0126
Philadelphia, PA	0.688	0.404	0.284
Phoenix, AZ	0.800	0.771	0.0287
Pittsburgh, PA	0.767	0.590	0.177
Portland, OR	0.726	0.598	0.128
Raleigh, NC	0.795	0.785	0.00986
Richmond, VA	0.811	0.777	0.0343
Sacramento, CA	0.768	0.731	0.0362
Salt Lake City, UT	0.778	0.734	0.0435
San Antonio, TX	0.891	0.849	0.0413
San Diego, CA	0.807	0.753	0.0546
San Francisco, CA	0.699	0.424	0.275
Seattle, WA	0.648	0.442	0.205
St. Louis, MO	0.811	0.761	0.0502
St. Petersburg, FL	0.852	0.838	0.0145
Tampa, FL	0.851	0.841	0.0103
Tucson, AZ	0.816	0.783	0.0327
Tulsa, OK	0.860	0.854	0.00611
Virginia Beach, VA	0.814	0.814	2.60e-05
Washington, DC	0.655	0.392	0.263
Average	0.794	0.717	0.0772

Notes: The table shows the CBD labor-supply measure derived from the model for each city, overall, Θ_{j^*}, and by mode, $\Theta^C_{j^*}$ and $\Theta^P_{j^*}$.

TABLE C.6: COUNTERFACTUAL CHANGES IN CBD LABOR SUPPLY

City	$\omega^P_{0,15}, \omega^C_{0,15}$	$\omega^P_{0,15}$	$\omega^P_{15,30}, \omega^C_{15,30}$	$\omega^P_{15,30}$	$\omega^P_{30,45}\omega^C_{30,45}$	$\omega^P_{30,45}$	$\omega^P_{45,60}\omega^C_{45,60}$	$\omega^P_{45,60}$	$\mathcal{A}^P_{0,15}, \mathcal{A}^C_{0,15}$	$\mathcal{A}^P_{0,15}$	$\mathcal{A}^P_{30,45}, \mathcal{A}^C_{30,45}$	$\mathcal{A}^P_{30,45}$
Albany, NY	1.02	1.00	1.05	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Atlanta, GA	1.02	1.00	1.04	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Austin, TX	1.03	1.00	1.04	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Birmingham, AL	1.05	1.00	1.04	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Boston, MA	1.01	1.00	1.04	1.02	1.04	1.02	1.02	1.01	1.00	1.00	1.00	1.00
Buffalo, NY	1.03	1.00	1.05	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Charlotte, NC	1.03	1.00	1.05	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Chicago, IL	1.02	1.00	1.03	1.02	1.03	1.02	1.02	1.01	1.00	1.00	1.00	1.00
Cincinnati, OH	1.01	1.00	1.05	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Cleveland, OH	1.01	1.00	1.05	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Columbus, OH	1.02	1.00	1.06	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Dallas, TX	1.02	1.00	1.05	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Denver, CO	1.00	1.00	1.05	1.00	1.04	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Detroit, MI	1.01	1.00	1.05	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Fresno, CA	1.06	1.00	1.03	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hartford, CT	1.04	1.00	1.03	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Houston, TX	1.03	1.00	1.05	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Indianapolis, IN	1.01	1.00	1.06	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Jacksonville, FL	1.01	1.00	1.05	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
AKansas City, MO	1.01	1.00	1.06	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Las Vegas, NV	1.05	1.00	1.05	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Los Angeles, CA	1.02	1.00	1.05	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Louisville, KY	1.02	1.00	1.06	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Memphis, TN	1.04	1.00	1.05	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Miami, FL	1.02	1.00	1.04	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Milwaukee, WI	1.03	1.00	1.05	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Minneapolis, MN	1.02	1.00	1.05	1.00	1.02	1.01	1.01	1.01	1.00	1.00	1.00	1.00
Nashville, TN	1.03	1.00	1.04	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
New Haven, CT	1.03	1.00	1.05	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
New Orleans, LA	1.06	1.00	1.03	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00
New York, NY	1.00	1.00	1.03	1.02	1.04	1.03	1.03	1.03	1.00	1.00	1.00	1.00
Oklahoma City, OK	1.02	1.00	1.06	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Orlando, FL	1.02	1.00	1.05	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Philadelphia, PA	1.02	1.00	1.05	1.02	1.02	1.01	1.01	1.01	1.00	1.00	1.00	1.00
Phoenix, AZ	1.00	1.00	1.05	1.00	1.04	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Pittsburgh, PA	1.02	1.00	1.04	1.01	1.03	1.01	1.01	1.01	1.00	1.00	1.00	1.00
Portland, OR	1.01	1.00	1.05	1.01	1.03	1.01	1.01	1.00	1.00	1.00	1.00	1.00
Raleigh, NC	1.01	1.00	1.04	1.00	1.04	1.00	1.02	1.00	1.00	1.00	1.00	1.00
Richmond, VA	1.03	1.00	1.05	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Sacramento, CA	1.04	1.00	1.04	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Salt Lake City, UT	1.02	1.00	1.06	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00
San Antonio, TX	1.04	1.00	1.05	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
San Diego, CA	1.04	1.00	1.04	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00
San Francisco, CA	1.02	1.00	1.05	1.02	1.02	1.01	1.01	1.01	1.00	1.00	1.00	1.00
Seattle, WA	1.01	1.00	1.05	1.01	1.03	1.01	1.01	1.01	1.00	1.00	1.00	1.00
St. Louis, MO	1.02	1.00	1.05	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
St. Petersburg, FL	1.05	1.00	1.03	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Tampa, FL	1.02	1.00	1.04	1.00	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00
Tucson, AZ	1.03	1.00	1.05	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Tulsa, OK	1.02	1.00	1.06	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Virginia Beach, VA	1.05	1.00	1.05	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Washington, DC	1.01	1.00	1.04	1.01	1.03	1.02	1.02	1.01	1.00	1.00	1.00	1.00
Average	1.02	1.00	1.05	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00

Notes: The table shows the counterfactual change in the CBD labor-supply measure, Θ_{j^*}, in response to counterfactual 10% increases in population density within various accessibility-zone areas (Columns 2-9) and in response to 10% increases in various accessibility-zone areas.