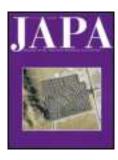
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b University of Washington

Does Accessibility Require Density or Speed?

A Comparison of *Fast* Versus *Close* in Getting Where You Want to Go in U.S. Metropolitan Regions

Jonathan Levine, Joe Grengs, Qingyun Shen, and Qing Shen

Problem, research strategy, and findings: Advocates of accessibility as a transportation performance metric often assert that it requires higher density. Conversely, traditional transportation planning methods have valued speed per se as an indicator of success in transportation. In examining these claims, we make two methodological innovations. The first is a new intermetropolitan gravity-based accessibility metric. Second, we decompose the impact of density on accessibility to highlight the distinct opposing influences of speed and proximity in a manner that illustrates different families of relationships between these two factors. This reveals that denser metropolitan regions have slower travel speeds but greater origin-destination proximity. The former effect tends to degrade accessibility while the latter tends to enhance it. Despite theoretical reasons to expect that the speed effect dominates, results suggest that the proximity effect dominates, rendering the denser metropolitan areas more accessible.

Takeaway for practice: Having destinations nearby, as when densities are high, offers benefits even when the associated congestion slows traffic. Where land use policy frequently seeks to support low-development densities in part in an attempt to maintain travel speeds and forestall traffic congestion, our findings suggest that compact development can often improve transportation outcomes.

n experienced Australian traveler once said that on business trips to Australian cities he could reckon to make four meetings in a day," writes Thomson (1977, p. 48). "In Europe he could manage five; in the United States he could manage only three." The reason behind the variations in this traveler's itineraries was not an American propensity for long meetings, or the speed of travel in American cities, which is in any case faster than in Western Europe or Australia (Kenworthy & Laube, 2002). Instead, his schedules were determined by the great distances, and, hence, long travel times separating his business contacts in metropolitan areas of the United States. What the traveler wanted was interaction in the form of personal contact with the people with whom he did business. The speed with which he was able to travel was relatively unimportant to him; much more central was the amount of interaction he could accomplish in a given time.

Keywords: accessibility, mobility, speed, proximity, transportation planning

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This traveler was unwittingly expressing a view of transportation policy based in accessibility, in contrast to the mobility-centered view so dominantly reflected in current policy and in the physical form of the built environment in metropolitan areas in the United States and many countries around the world. This mobility-oriented view extends to the metrics by which transportation systems are assessed. When evaluating the performance of a transportation system, the fundamental criterion for success has long been faster vehicle operating speed (Ewing, 1995; Transportation Research Board, 2010). Common indicators include delay per capita, dollars wasted while waiting in traffic (Schrank & Lomax, 2007), and highway level of service (Edwards, 1992; Transportation Research Board, 1994). This mobility-based perspective of transportation policy dominates the view of the general public as well. The widely publicized congestion measures that routinely appear in newspapers nationwide when the Texas Transportation Institute publishes its annual Urban Mobility Report (Schrank & Lomax, 2007) have helped to elevate the alleviation of traffic congestion to a top public policy priority. Under all such mobility-based evaluation measures, planners, engineers, and the general public deem rapid movement as a definitive success.

Yet, a building block of modern transportation planning is the notion that the demand for transportation is derived (Meyer & Miller, 2001); that is, people rarely consume transportation for the pleasure of movement per se, but rather travel in order to reach opportunities available at destinations. This fundamental understanding is an underpinning of travel demand analysis, which models transportation flows based on the arrangement of land use patterns across a region (Mitchell & Rapkin, 1954). Despite some speculation that some market segments may view movement as an end in itself (Salomon & Mokhtarian, 1998), the derived demand hypothesis remains the consensus of the field, a view supported by the preponderance of empirical evidence.

Apart from its role in land use-based travel demand analysis, the derived demand assumption has another important implication, which transportation policy has too rarely confronted. If the purpose of transportation is not movement but access, then increased mobility is desired only to the extent that such a change also increases accessibility over the longer run. Pursuit of congestion relief through added transportation capacity can induce destinations to move farther and farther apart (Transportation Research Board, 1995). In theory, a paradox can, thus, arise: Increased mobility can be associated, over the long run, with more time and money spent in travel, rather

than less. Travel to more remote shopping or work locations might be accomplished at a high speed, but the spread of these destinations can demand more travel compared to more compact and clustered urban arrangements where travel is slower. If travelers do not consume transportation for its own sake but in order to access destinations, then policies that lead to increased costs per destination would be counterproductive because they would leave the travelers with less time and money to spend at their destinations. This formulation implies a rejection of mobility or congestion relief per se as an independent goal for transportation policy. The goal is more properly specified as accessibility, which has been defined as the "potential of opportunities for interaction" (Hansen, 1959, p. 79) or the "ease of reaching places" (Cervero, 1996, p. 1). Mobility, by contrast, is simply the ease of movement. Where destinations are nearby, high accessibility can be provided even with low mobility (as the Australian business traveler found in the compact cities of Europe); conversely, where origins and destinations are spread broadly, even great mobility does not ensure high accessibility. Thus, reliance on metrics of mobility to evaluate planning outcomes implies either a belief that the proximity of origins and destinations is insensitive to transportation system changes, or that such proximity is irrelevant as a planning outcome.

Mobility is one means to accessibility; others are remote connectivity (e.g., via Internet or other electronic means) and proximity (Figure 1). But mobility and proximity exist in tension with each other: Places with many origins and destinations near one another tend to be places where surface transportation is slow; conversely, areas of rapid surface travel tend to be areas where origins and destinations are further apart. It is not immediately apparent which urban forms offer higher accessibility: areas of rapid surface travel and little proximity, or areas offering high proximity of origins and destinations but slower travel. Accessibility impacts would be the result of the net effect of speed and distance change as one moves from one urban form to the other.

Nearly all empirical research measuring accessibility to date has been focused on case studies of single metropolitan regions (e.g., Benenson, Rofe, Martens, & Kwartler, 2010; Cheng, Bertolini, & le Clercq, 2007; Grengs 2010; Scott & Horner, 2008; Shen, 1998). Allen, Liu, & Singer (1993) compared accessibility between metropolitan areas but used standard speeds by roadway type as the basis of their impedance metric; as such their study would not have captured the tradeoff between proximity and travel speed. More recently, Kawabata and Shen (2006) compared Boston and Los Angeles with Tokyo in terms of job accessibility; their analysis focused on the accessibility gap

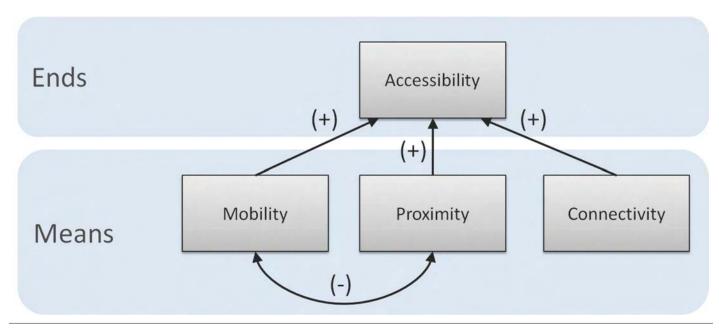


Figure 1. Relationships among mobility, proximity, connectivity, and accessibility.

between automobile commuters and public transit commuters rather than the relative contributions of proximity and speed. Accessibility comparisons could be on the basis of the same region or regions over time (e.g., Grengs, 2004) or between regions in a cross-sectional analysis. This study adopted the cross-sectional approach. One consideration in this design was data availability: Outputs of regional travel models are rarely archived, and generating an ample basis for comparison would be difficult. The second consideration pertained to sources of variation. Metropolitan regions grow incrementally, so their urban form does not change radically from one decade to the next. For this reason, a time-series comparison would have limited variance between observations. By contrast, a cross-sectional comparison makes use of existing variance in urban form between metropolitan areas in order to infer relationships with accessibility outcomes.

Accessibility has been operationalized in a variety of ways. A study by Wachs and Kumagai (1973) is an example of a cumulative opportunities approach, where accessibility is defined by the count of destinations that fall within a threshold distance or travel time from any zone. Niemeier (1997) provides an example of a utility approach, where accessibility is defined in terms of the value that travelers assign to their trip to work. Other approaches include accounting for travelers' time constraints based on the work of Hägerstrand's (1970) time-space theory (e.g., Kwan, 1998; Miller, 1999), and incorporating dimension of overcoming social exclusion (e.g., Hine & Mitchell, 2001). The current study distinguishes accessibility and

mobility much more narrowly. A *mobility improvement* is defined here as a reduction in the time-plus-money cost of travel per mile. An *accessibility improvement* is approximately defined as a reduction in the time-plus-money cost of travel per destination. But, since not all destinations are equal, one should speak of the value of destinations; and, since accessibility can also be gained by virtual means, "travel" should be replaced by the broader "interaction." Thus, an accessibility improvement is defined here as a reduction in the time-plus-money cost of interaction per unit value of destination.

One view in the urban planning and transportation literature holds that a low-density, auto-oriented metropolitan form is also a low-accessibility form (Curtis & Scheurer, 2010; Ewing, 1994). The implications of this view are far reaching. A mobility-based transportationplanning logic frequently militates towards development of low-density areas that support rapid highway travel. If these forms of development turn out to degrade metropolitan accessibility overall, metropolitan density would be seen as a (accessibility-based) transportation benefit, rather than a (mobility-based) transportation disadvantage. The problem is that the assertion that low-density, auto-oriented development is a low-accessibility form has little basis in empirical analysis. It is certainly not true by definition; it may well be that more rapid travel in low-density metropolitan regions more than compensates for the great distances between their origins and destinations.

This study seeks to support policy reform by developing and estimating measures of accessibility that enable a

meaningful comparison between multiple metropolitan areas of the United States. The indicators, which can be analyzed both within and between regions, can help gauge the progress of policy on infrastructure and the built environment. This study focuses on accessibility to work by automobile with an analysis of 38 of the largest metropolitan areas of the United States. It first demonstrates, using pairwise comparisons of similar metropolitan regions, that regional accessibility can be decomposed into speed and proximity effects, showing how some regions favor one over the other. It then investigates the metropolitan urban form conditions that might provide a high level of accessibility to its residents and finds that density is a key factor, even though it has contradictory effects on accessibility through both the speed and proximity effects.

Study Approach

This study bases its accessibility metrics in the gravity model (Isard, 1960; Wilson, 1971), a powerful conceptual tool, which simultaneously accounts for both the transportation network and its surrounding land use conditions (Handy & Niemeier, 1997). Measures of accessibility derived from a gravity model are commonly used by urban planning scholars to evaluate the relative ease of reaching spatially distributed opportunities in a metropolitan region (Cervero, Rood, & Appleyard, 1999; Grengs, 2010; Shen, 1998). Under a gravity-based measure, the higher the accessibility index the greater the advantage a person has in reaching destinations. A person living in a zone with a high value either has more destinations nearby or is capable of traveling more quickly to distant destinations, compared to a person living in a zone with a lower value. A gravity model measures the potential for a person to reach destinations, but it does not address whether people actually choose to seize that potential. Nevertheless, we prefer this measure over a range of others (Handy & Niemeier, 1997) because it allows for decomposing accessibility into the speed and proximity effects and because it best matches the core policy tasks of the urban planner: planning land use and transportation systems for a broad range of constituents with many diverging preferences. The study uses a common form of the gravity model proposed by Hansen (1959):

$$(A_i) = \sum_j O_j F(c_{ij}) \tag{1}$$

where:

(A_i) is the accessibility index for people living in zone I, for travel to work by automobile;

- O_j is the number of opportunities (the sum of jobs) in destination zone j; and
- $F(c_{ij})$ is a composite impedance function capturing travel conditions across multiple metropolitan areas, associated with the cost of travel c for travel between zones i and j.

Zone-to-zone travel time and trip flow tables were requested from the metropolitan planning organizations (MPO) of the largest 50 regions in the United States. This study is based on 38 metropolitan regions, as listed in Table 1, that responded with data sufficient to analyze.

Table 1. Metropolitan regions included in the study.

Los Angeles 2 12,874,797 Chicago 3 9,580,567 Dallas 4 6,447,615 Philadelphia 5 5,968,252 Houston 6 5,867,489 Washington, DC 8 5,476,241 Atlanta 9 5,475,213 Boston 10 4,588,680 Detroit 11 4,403,437 Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 <tr< th=""><th>Metropolitan region</th><th>Population rank</th><th>2009 MSA population</th></tr<>	Metropolitan region	Population rank	2009 MSA population
Chicago Dallas A Chicago Dallas A Chicago Dallas A Charlotte Artlanta A Cleveland Corlando Co	New York	1	19,069,796
Dallas 4 6,447,615 Philadelphia 5 5,968,252 Houston 6 5,867,489 Washington, DC 8 5,476,241 Atlanta 9 5,475,213 Boston 10 4,588,680 Detroit 11 4,403,437 Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis	Los Angeles	2	12,874,797
Philadelphia 5 5,968,252 Houston 6 5,867,489 Washington, DC 8 5,476,241 Atlanta 9 5,475,213 Boston 10 4,588,680 Detroit 11 4,403,437 Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Charlotte 33 1,745,524 Indianapolis 34 1,743,658	Chicago	3	9,580,567
Houston 6 5,867,489 Washington, DC 8 5,476,241 Atlanta 9 5,475,213 Boston 10 4,588,680 Detroit 11 4,403,437 Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Dallas	4	6,447,615
Washington, DC 8 5,476,241 Atlanta 9 5,475,213 Boston 10 4,588,680 Detroit 11 4,403,437 Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis <td>Philadelphia</td> <td>5</td> <td>5,968,252</td>	Philadelphia	5	5,968,252
Atlanta 9 5,475,213 Boston 10 4,588,680 Detroit 11 4,403,437 Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Houston	6	5,867,489
Boston 10 4,588,680 Detroit 11 4,403,437 Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond <td>Washington, DC</td> <td>8</td> <td>5,476,241</td>	Washington, DC	8	5,476,241
Detroit 11 4,403,437 Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma C	Atlanta	9	5,475,213
Phoenix 12 4,364,094 San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hart	Boston	10	4,588,680
San Francisco 13 4,317,853 Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New	Detroit	11	4,403,437
Seattle 15 3,407,848 Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffa	Phoenix	12	4,364,094
Minneapolis 16 3,269,814 San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Roche	San Francisco	13	4,317,853
San Diego 17 3,053,793 Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Seattle	15	3,407,848
Baltimore 20 2,690,886 Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Minneapolis	16	3,269,814
Denver 21 2,552,195 Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	San Diego	17	3,053,793
Portland 23 2,241,841 Cincinnati 24 2,171,896 Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Baltimore	20	2,690,886
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Cleveland 26 2,091,286 Orlando 27 2,082,421 San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Portland	23	2,241,841
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San Antonio 28 2,072,128 Kansas City 29 2,067,585 Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Cleveland	26	2,091,286
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Las Vegas 30 1,902,834 Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	San Antonio	28	2,072,128
Columbus 32 1,801,848 Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Kansas City	29	2,067,585
Charlotte 33 1,745,524 Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Las Vegas	30	1,902,834
Indianapolis 34 1,743,658 Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Columbus	32	1,801,848
Virginia Beach 36 1,674,498 Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Charlotte	33	1,745,524
Nashville 38 1,582,264 Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Indianapolis	34	1,743,658
Memphis 41 1,304,926 Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Virginia Beach	36	1,674,498
Louisville 42 1,258,577 Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Nashville	38	1,582,264
Richmond 43 1,238,187 Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Memphis	41	1,304,926
Oklahoma City 44 1,227,278 Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Louisville	42	1,258,577
Hartford 45 1,195,998 New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Richmond	43	1,238,187
New Orleans 46 1,189,981 Buffalo 50 1,123,804 Rochester 51 1,035,566	Oklahoma City	44	1,227,278
Buffalo 50 1,123,804 Rochester 51 1,035,566	Hartford	45	1,195,998
Rochester 51 1,035,566	New Orleans	46	1,189,981
	Buffalo	50	1,123,804
Tucson 52 1,020,200	Rochester	51	1,035,566
	Tucson	52	1,020,200

Although the larger study on which this article draws developed work and non-work accessibility metrics for both auto and transit modes, this article focuses on work accessibility by car. Work destinations were selected as the basis for accessibility calculations because they can be readily aggregated and compared; by contrast the various non-work destinations have radically different meaning and values to the traveler, requiring further assumptions and analysis before they can be analyzed jointly. The auto mode was selected for focus due to the dominance of auto travel in commuting, which also makes it more influential in terms of policy relevance

The $F(c_{ij})$ parameter in Equation 1 requires explanation for making comparisons across metropolitan regions. The term is equal to $\exp(-\beta T_{ij})$, where \exp is the base of natural logarithms, β is a parameter empirically derived to maximize the fit between predictions of the gravity model and observed distributions of travel times. The β term ordinarily varies between metropolitan regions and has an important interpretation. People's willingness to travel a given time differs from region to region: in some, a 20-minute trip would be considered long and would be avoided if possible; in others, it would be considered to be a short trip. The value of β would be lower in the latter region than in the former, indicating a lower impedance associated with each minute of travel.

Willingness to travel is a function of the opportunities available. Regions in which many destinations were close by and few far away would presumably demonstrate greater reticence to travel (and, thus, a higher value for β) than those with few nearby destinations and many farther away. In order to compare accessibility between regions, this study considered two possibilities: a β term that varies between regions and a single β term across all comparison regions. The former would have accounted for interregional variations in propensity to travel; the latter would aid consistent comparison of accessibility between regions.

This study uses the single β option. Variations in β are largely endogenous to land use patterns, as described above. For this reason, using region-specific parameters would have the effect of giving accessibility credit to a region in which people readily take long trips. But if their propensity to take long trips is a function in part of lack of nearby destinations, then the region-specific parameter would tend to overestimate the accessibility of these places compared to others where long-distance trips were less necessary. The search for a single aggregate β was necessary in order to reach meaningful comparisons of accessibility between regions. Note that even a single regional β term is in effect a composite of numerous and varying β terms for individuals within the region. The process of aggregation

here is not new; where most travel modeling suffices with a β aggregated to the regional level, this project required a higher level of aggregation.

The goal of using a single β term across all regions in order to achieve a consistent comparison of accessibility among metropolitan regions was complicated by a lack of data. Ideally, we would derive a β term for each individual region separately and then estimate a shared β based on these region-specific values. Unfortunately, only 16 of the 38 MPOs were able to provide the interzonal data β including travel times and the number of trips, that are required to estimate a region-specific β parameter.² However, the β parameters for these 16 metropolitan regions are negatively correlated with metropolitan population, so we applied a regression model to estimate β parameters across the full set of 38 regions based on metropolitan population.³ The relationship between β and population among the 16 regions is nonlinear, so the following regression equation uses an exponential function as the bestfitting approximation of the relationship.

$$\beta = a \times EXP(b \times POP) \tag{2}$$

where:

 β is the dependent variable in the regression model and is the parameter described in Equation 1, an empirically derived value for each of 16 metropolitan regions; POP is the independent variable in the regression model and is the MPO population in 2000 based on census data;

a and b are parameters in an exponential equation to be estimated by regression.

Equation 2 is run using values from 16 regions for two cases of trip purpose, resulting in estimates for the regression model parameters for work travel (a = 0.109, b = -3.52×10^{-8}). These results were then used to predict the β values for each of the 38 metropolitan regions. Finally, we assigned as the single, shared β value the result from the metropolitan region with the median MPO population and used it for the calculation of accessibility indicators for each of the 38 metropolitan regions.

Evaluating the Interaction of Speed and Proximity: Pairwise Comparisons of Metropolitan Regions

Understanding region-level tradeoffs between speed and proximity requires intermetropolitan comparisons of accessibility. In order to explore the interaction of speed and proximity on accessibility, metropolitan areas were paired on the basis of population size, and the distribution of accessibility analyzed between the two regions. For example a pairing of metropolitan Washington, DC, with the San Francisco Bay Area (Figure 2) reveals similar levels of accessibility at the low end (the 1st percentile household) and the high end (e.g., the 99th percentile household). The rest of the distribution reveals a higher accessibility for the San Francisco area; for example, with an accessibility score of over 100,000, the median Bay Area resident enjoys nearly double the accessibility of his or her Washington, DC, counterpart. Although the horizontal axis in these graphs is ordered simply by population percentile of the accessibility score, it has somewhat of a geographical interpretation: since accessibility generally declines in concentric rings radiating outward from the center of the region, households at the low end of the distribution tend to reside in peripheral areas, while those at the high end live at the center. The median household would in most cases be a suburban resident.

Accessibility differences between two regions may be decomposed into a proximity component and a speed component (Grengs, Levine, Shen, & Shen, 2010). This is

accomplished by transforming the speed distribution of San Francisco into that of Washington, DC. A new set of accessibility indicators is calculated for San Francisco, using travel times derived from Washington speeds.⁴ Figure 2 graphs the transformed accessibility curve together with the original curves. The speed-related advantage to San Francisco is shown as the shaded area between the top and bottom curves; the proximity-related advantage to Washington, DC, is represented by the crosshatched area below the bottom curve. Notwithstanding the greater density of the San Francisco Bay Area, Washington, DC, demonstrates both a proximity advantage and a speed disadvantage. Given the greater magnitude of the speed disadvantage of Washington, DC, the potential accessibility benefit of greater proximity was squandered by poor mobility relative to that of the San Francisco Bay Area, in this case automobility, since the accessibility metric is automobile based. Here, the accessibility outcome is consistent with traditional mobility-based transportation planning; poor mobility has degraded the accessibility of what might otherwise be a highly accessible metropolitan area.

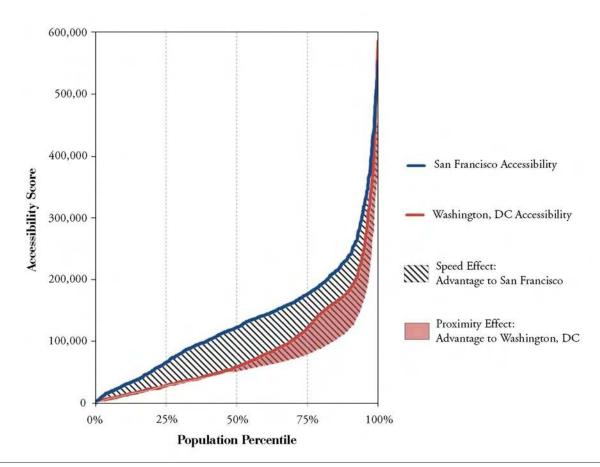


Figure 2. Decomposition of accessibility differences between metropolitan San Francisco and Washington, DC.

(Color figure available online.)

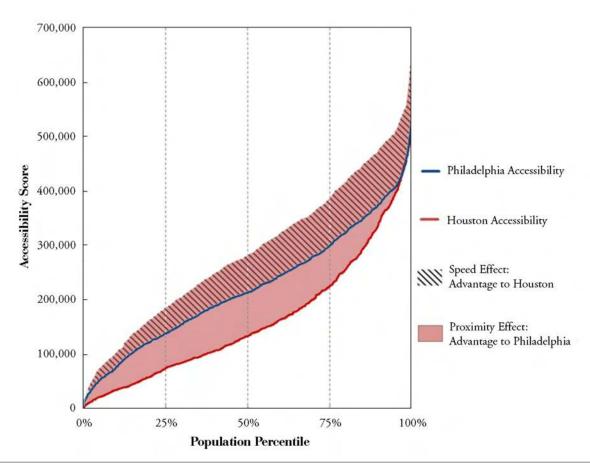


Figure 3. Decomposition of accessibility differences between metropolitan Philadelphia and Houston. (Color figure available online.)

This relationship of speeds and accessibility is not universal, however, as illustrated by a similar decomposition of accessibility differences between another pair of similarly sized metropolitan areas: Philadelphia and Houston (Figure 3). Philadelphia enjoys a considerable accessibility advantage over Houston for most of the population distribution, notwithstanding the similar densities of the regions overall (1,038 people/km² for Houston, 1,070 for Philadelphia). A decomposition of the accessibility between the two regions reveals that Houston enjoys a considerable speed advantage over Philadelphia, but suffers from a proximity disadvantage. Notably, the proximity disadvantage exceeds the speed advantage, generating an accessibility disadvantage for Houston overall. While the Washington-San Francisco comparison was consistent with a mobility-based view of planning, the Houston-Philadelphia comparison provides a counterexample: Houston accessibility suffers when compared to Philadelphia despite its faster travel speeds.

A third case presents itself as well: If metropolitan region A enjoys both a speed and a proximity advantage over region B, it will demonstrate higher accessibility overall. This is the case with New York when compared with Los Angeles (Figure 4). New York enjoys a slight speed advantage, a considerable proximity advantage, and overall accessibility advantage over Los Angeles for most of the population distribution. Ironically, New York was singled out as a particularly problematic case in a recent book, *Mobility First* (Staley, 2008). Notwithstanding the serious congestion problems of New York City, its region presents the highest accessibility case of all regions studied (a function in part of its very large size). This case demonstrates the very different conclusions that are reached in transportation policy when the evaluation turns from mobility to accessibility; a region deemed to be mobility-deficient emerges as accessibility rich.

Accessibility and Urban Form

A central question of this study is the impact of urban form on accessibility outcomes, and in particular, what kind of metropolitan region provides a high level of accessibility to its residents. *Urban form* in this context can

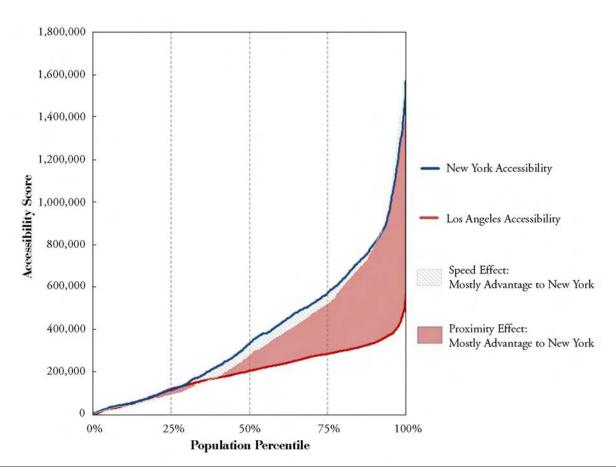


Figure 4. Decomposition of accessibility differences between metropolitan New York and Los Angeles. (Color figure available online.)

mean a host of characteristics, including centralization, concentration, density, and others (Galster, Hanson, Ratcliffe, Wolman, Coleman, & Freihage, 2001; Lee, 2007). This study tested the impacts of a range of these attributes on accessibility outcomes (measured in this section as median work accessibility by auto). Regression models revealed little to no relationship between such metrics as centralization and concentration but that average metropolitan densities appeared to be a significant determinant of median work accessibility by automobile. The discussion that follows is an effort to discover a theoretical basis for this apparent relationship between metropolitan densities and accessibility.

The finding that several common urban form indicators have little relationship to regional accessibility is, in part, a function of a focus on the median resident. The median resident in accessibility terms of the typical U.S. metropolis is a suburbanite (in each of the 38 regions, the zone with the median accessibility score is located outside the central city, and in many instances at a substantial distance from the central city). In nearly every case, this individual does not live in or near the downtown or even in or near a suburban

concentration such as a downtown or transit-oriented development. Thus, the extent of these concentrations affects this person only marginally. By contrast overall metropolitan densities can affect median accessibility markedly in two ways.

- Higher density can reduce average travel speed. Autoownership rates in U.S. metropolitan regions, including higher-density regions, is high. Thus, population density in these regions can lead to high traffic densities and therefore slow speed. By holding distances constant, slower travel speeds would degrade accessibility.
- Higher density can increase proximity, by shortening the distance between origins and destinations. Higher density regions put numerous destinations closer to a given origin than their lower-density counterparts. For example, in the case of jobs, higher job densities would mean more job locations at closer proximity to more residents. By holding travel speeds constant, shorter distances would increase accessibility.

Thus, the effect of density on accessibility can be thought of as the sum of the speed effect and the proximity effect. If the speed effect dominates, denser regions would be less accessible regions; if the proximity effect dominates, less accessible regions would be more accessible.

There are theoretical reasons to argue both positions, as described below.

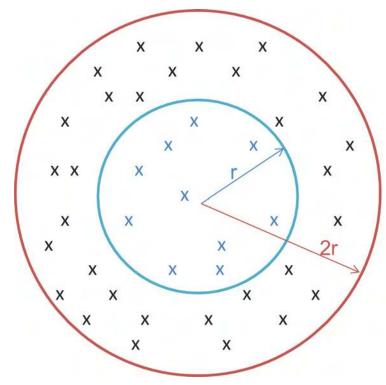
Possibility 1: The Speed Effect Dominates the Proximity Effect

One common measure of accessibility is a cumulative opportunities measure, or the number of destinations reachable within a given amount of time. This concept is used here to illustrate why the speed effect may dominate in producing higher accessibility. The territory accessible within Y minutes would be an irregularly shaped area (depending on the shape of the street network) but is simplified here as a circle and illustrated with Figure 5. Destinations are represented in the figure as Xs. When speed doubles, the radius of the circle that can be reached within a given time increases from r to 2r. As a consequence, the area of the circle quadruples from πr^2 to $4\pi r^2$. Given constant density of the destinations, the destinations reachable within the specified time also quadruple with the doubling of speeds. Thus, in the case of the simple circle, accessibility increases with the square of speed.

The impact of increasing densities on accessibility can be illustrated in a similar fashion. In Figure 6, speeds are held constant, but density of destinations is doubled, leading to a doubling of accessibility. Thus, while accessibility increases with the square of speed, it increases linearly with density. Increasing speed, thus, confers a very significant accessibility advantage, one that will be difficult to overcome with the proximity effect. This theoretical possibility supports the mobility-centered view that is reflected so dominantly in current transportation policy, but there is another possible explanation of density's influence on accessibility.

Possibility 2: The Proximity Effect Dominates the Speed Effect

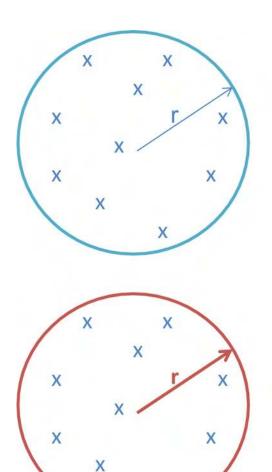
Notwithstanding the very evident benefit of speeds in producing accessibility, could the proximity effect dominate the speed effect? This possibility is analyzed by decomposing the relationship between density and transportation speeds. Metropolitan density may influence travel speeds in two competing ways. First, low-density metropolitan regions typically offer more roadway capacity per person than their high-density counterparts. Figure 7 shows that low-density regions tend to have a high ratio of roadway lane miles per capita, a factor that would tend to raise travel speeds. Yet, the tendency for higher capacity in low-density regions appears to be at least partly negated by the higher vehicle miles traveled (VMT) per capita observed in these regions, as shown in Figure 8. Low-density regions are thus



	Radius	Area	Density	Destinations or Accessibility
Blue Circle	r	πr ²	10/πr ²	10
Red Circle	2r	4πr ²	10/πr ²	40

^{*} Note: one x represents one destination.

Figure 5. Illustration of speed effect of accessibility (holding destinations constant).



	Radius	Area	Density	Destinations or Accessibility
Blue Circle	r	πr ²	10/πr²	10
Red Circle	r	πr ²	20/πr ²	20

* Note: one x represents one destination.

Figure 6. Illustration of density effect of accessibility (holding speeds constant).

(Color figure available online.)

simultaneously roadway-intensive and travel-intensive. Speeds are determined neither by VMT nor by roadway miles in isolation, but as a function of the interaction of the two. The relatively strong ($R^2 = 0.26$) negative relationship between density and VMT per capita interacts with a somewhat stronger ($R^2 = 0.37$) relationship between density and freeway lane miles per capita. The net result is that the relationship between population density and traffic density (Figure 9) is relatively weak ($R^2 = 0.11$). Lower-density regions show less traffic density than higher-density counterparts, but only marginally. While the speed-accessibility link is expected to be strong, the density-speed link may be quite weak, and by extension lead to a weak link between density and accessibility. In this case, the proximity effect would outweigh the speed effect.

These relationships were tested by implementing a path analysis, using the 38 cases for which data were available. Path analysis is an application of multiple regression that aims to identify dependencies among a set of variables. It uses several regression equations in a recursive manner to

estimate a system of interrelated variables, and it is customary to represent the results graphically as shown in Figure 10. The values represented along each link in the figure are standardized regression coefficients, a measure of the strength of the relationship between the variables shown in the diagram. The dependent variable of each regression equation is the variable to which an arrow points. Independent variables are those represented as pointing toward the dependent. For example, weighted average auto speed is the dependent variable in a regression with highway speed limit and total daily VMT to total lane miles ratio independent.

Variables in Figure 10 are defined as follows:

Urban area density: Population of the relevant urban area divided by its total land area in square kilometers (U.S. Department of Transportation, Federal Highway Administration, 2008).

Proximity: Median gravity-based work accessibility when distance between origins and destinations (rather

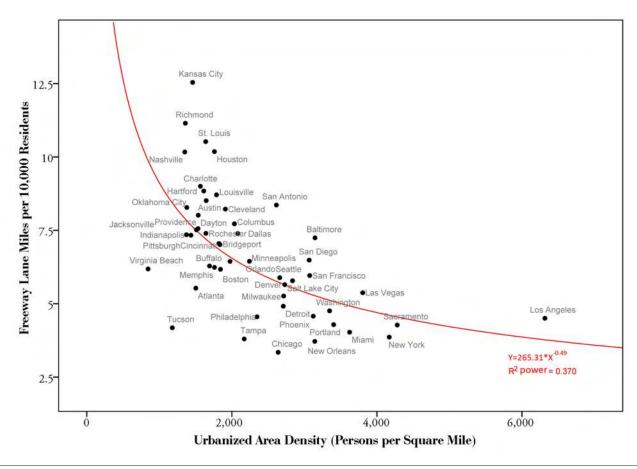


Figure 7. Urbanized area density and freeway lane miles per capita. Source: U.S. Department of Transportation, 2008.

than travel time) is used as the metric of impedance. *Accessibility:* As described above, calculated as a gravity metric with peak-period travel time by automobile between origins and destinations used as the metric of impedance. The variable is the median score for residents in the region.

Highway speed limit: The speed limit of the state or territory to which each metropolitan region belongs. Among the 38 MPOs in our study, this variable takes one of the three values, 65 mph, 70 mph, or 75 mph. Total daily VMT per capita: Total daily VMT by the residents of the urban area divided by the total population of the urban area, retrieved from highway statistics (U.S. Department of Transportation, Federal Highway Administration, 2008).

Total freeway lane miles per capita: Total freeway lane miles within the urban area divided by the total population of the urban area, retrieved from highway statistics (U.S. Department of Transportation, Federal Highway Administration, 2008).

Total daily VMT to total lane miles ratio: Total daily

VMT per capita divided by total freeway lane miles per capita.

Weighted average auto speed: This variable is the average speed, weighted by the imputed travel volume share for this zonal pair. The formula of calculating this weighted average auto speed is:

This computation can be broken into two parts, the travel speed for each pair: $\frac{D_{ij}}{T_{ij}}$, and its weight of imputed travel volume share: $\frac{D_{ij}}{P}$, $\frac{P_i}{W}$. $e^{-T_{ij} \cdot \beta}$, where, n is the number of TAZs in a metro; i is the origin TAZ; j is the destination TAZ; D_{ij} is the Euclidean distance between origin and destination; T_{ij} is the peak-hour travel time by automobile between origin and destination; p_i is the number of population in the origin TAZ; P is the total population in the metro; w_j is the number of work opportunities in the destination TAZ; W is the total number of work opportunities in the metro; $e^{-T_{ij} \cdot \beta}$ is the travel impedance, which is an

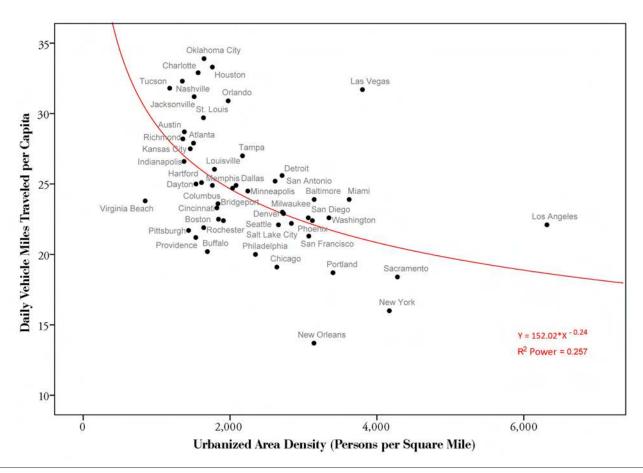


Figure 8. Daily vehicle miles traveled by urbanized area density, largest 50 U.S. urbanized areas. Source: U.S. Department of Transportation, 2008.

exponential function of T_{ij} and β , the pooled impedance factor for home-based work trips. The computation of imputed travel volume adopts the idea and format of the gravity model for trip generation and distribution commonly used in travel demand forecasting and modifies it to simplify the calculation.⁷

In path analysis (Figure 10), weights along sequential paths are multiplied to calculate the weight (or strength of relationship) along the entire link; weights of parallel paths are summed. Thus the weight from density to speed may be calculated as: $[(-0.537 \times -1.145) + (-0.448 \times 0.746)] \times (-0.440) = -0.123$. As predicted, this link is weak relative to the other links shown in Figure 10, a function of its incorporation of two countervailing factors: low density regions are freeway rich on a per capita basis, but these regions simultaneously demonstrate high VMT per capita.

As discussed above, the net effect of density on accessibility is the sum of the positive effect of greater proximity evident in denser areas and the negative effect of these

areas' slower speeds. This effect may be analyzed by comparing the composite weight along right hand path (via proximity) and the left-hand path (via speed). The weight along the entire speed path equals $(-0.123 \times 0.271) = -0.033$, while that along the proximity path equals $(0.587 \times 0.720) = 0.423$. Thus, notwithstanding the evident advantages of speed in generating accessibility, density exerts a positive accessibility effect via proximity that is over 10 times as strong as the negative effect via density.

These results, with the positive impacts of density on auto accessibility outweighing their negative impacts, are corroborated by data shown in Figure 11. Overall, the figure demonstrates a positive relationship between urbanized area density and accessibility. There is some correlation between density and metropolitan size (New York and Los Angeles are simultaneously two of the largest and densest regions) but the positive relationship holds even without these cases. For example, the small region of Las Vegas demonstrates high accessibility, in part a function of its development density.

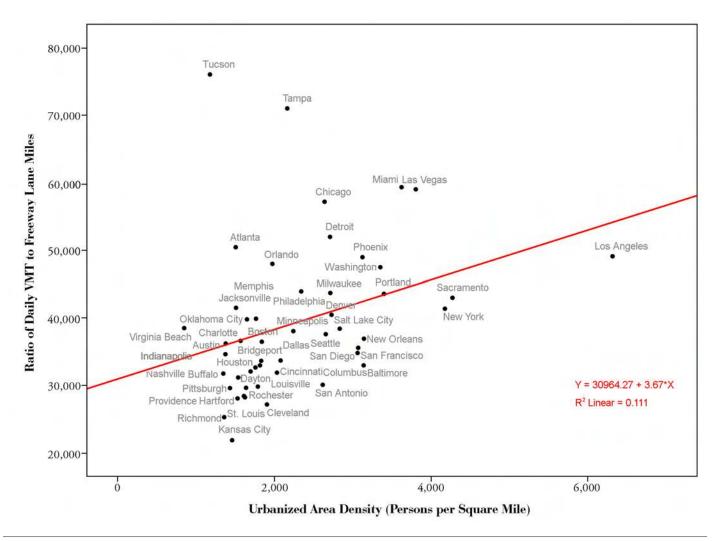


Figure 9. Traffic density by population density. Source: U.S. Department of Transportation, 2008.

Conclusion

This study was designed in part to provide proof of the concept that intermetropolitan comparisons of accessibility are feasible. The metrics for comparing transportation outcomes between regions presented here stand in contrast to the strictly mobility-based evaluation approaches that typify traditional transportation planning. Accessibility metrics, while increasing in importance in transportation practice and research, are rarely used to compare metropolitan areas. Intermetropolitan comparisons are key to moving accessibility to a more central position in transportation policy. This is primarily because outcomes are frequently judged relative to others; professionals and lay people are both keen on asking how we are doing compared to others. Intermetropolitan comparison is also central to inferring the determinants of accessibility and accessibility change.

Two key obstacles to intermetropolitan comparison present themselves. The first is data availability and consistency. The principal data sets required for this current analysis are zone-to-zone travel times and travel flows for peak and off-peak periods by each metropolitan area. On the one hand, these data are developed by virtually all large U.S. metropolitan planning organizations as part of their regional transportation planning process. But the data are collected within a hodgepodge of categories and definitions. Much of the work of the current study was devoted to resolving intermetropolitan discrepancies in these datasets, a task that necessarily led to a comparison that is less reliable than it might be. Progress in accessibility evaluation will be facilitated by consistent definition of these model outputs across regions, and perhaps even the development of a nationwide repository of this information. This would have precedent in the National Transit Database, which requires standardized reporting on the

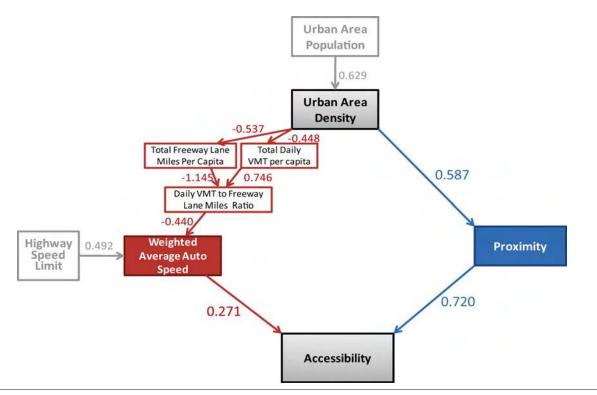


Figure 10. Path analysis of relationships of density, speed, proximity, and accessibility.

part of transit agencies receiving federal funding, a standardization that facilitates meaningful comparison between agencies.

The second obstacle to intermetropolitan comparison of accessibility is methodological. Whereas in standard transportation planning practice an individual impedance distance-decay function is estimated throughout the region, this study has relied on a single pooled factor. This article has argued both for the necessity and for the logic of such a move; yet, there are many approaches to estimating such a factor. Significantly higher or lower factors could not only raise or lower accessibility levels overall, but could alter the ordinal ranking between metropolitan areas.

In addition to demonstrating the feasibility of intermetropolitan comparisons of utility, this study seeks to demonstrate their relevance to urban planning practice. Traditional mobility-based transportation evaluations tend to militate against denser development on the theory that dense land use can lead to dense traffic and, hence, congestion. The analysis presented here does not dispute that, but argues for a more nuanced understanding of dense development: increasing density may well be accessibility enhancing, if the proximity effect on accessibility outweighs the speed-reduction effect. Conversely, using land use regulations to preclude such densification

may degrade accessibility even as it strives to enhance or maintain (auto)mobility. This study supports the view that low-density regions tend to be regions of low automobile accessibility as well. Where higher densities are frequently viewed as a transportation disadvantage because of their impacts on automobility, this study suggests distinct transportation advantages when viewed in accessibility terms.

Ultimately, reform of transportation planning toward an accessibility-oriented practice is about getting more of what people want out of transportation. This perspective brings transportation planning practice in line with transportation research that finds that the demand for travel is derived from the demand for reaching destinations. The shift holds the promise of altering the tradeoff relationship that has gripped transportation for years whereby transportation goals and environmental goals are viewed as being in competition. With compact metropolitan regions being associated with both lower VMT and higher accessibility, transportation and land use policy may be able to promote both sets of values simultaneously.

Notes

1. In other contexts, accessibility focuses on the needs of people with disability. The concept is used more broadly here.

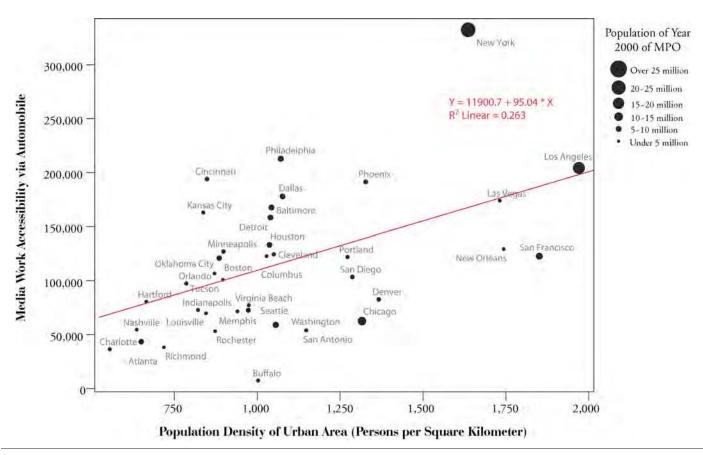


Figure 11. Median work accessibility by automobile by urbanized area density.

- 2. Complete data required for the calibration of a regional β include zone-to-zone travel times and trip flows for home-based work trips. Of the 38 MPOs, 22 provided either none or incomplete trip flow data.

 3. The 16 metropolitan regions are reasonably representative of the full set of 38 metros in terms of geography, density, and population: Bridgeport-Stamford, Chicago, Cincinnati, Dallas, Detroit, Hartford, Indianapolis, Los Angeles, Minneapolis–St. Paul, Philadelphia, Phoenix, Portland, San Diego, San Francisco, Seattle, and Washington, DC.

 4. As explained more fully in Grengs et al. (2010), the transformation is accomplished by calculating a z-score for each value in a zone-to-zone travel speed matrix from metro A. This z score matrix is then applied to the mean and standard deviation of speeds from Metro B to transform the speed distribution of Metro A into that of Metro B.
- **5.** The R^2 here is the product of the R^2 values from the two structural equations as shown in the path diagram: $0.26 \times 0.37 = 0.11$. That this relationship is weak is not surprising given the complexity with which traffic congestion is produced (Downs, 1992).
- **6.** The speed limit is an aggregate of all types of roads, including highways and local roads, and is intended to capture the effect of roadway speed limits as they contribute to the average transportation speeds of a metropolitan region.
- 7. In the widely used gravity model formula in travel demand forecasting (United States Department of Transportation, Federal Highway Administration and Urban Mass Transportation Administration, 1977), the number of trips between two areas is determined by the productions of the origin area and the attractions of the destination area, weighted

by the impedance between the two areas. The productions and attractions are estimated based on household income and travel information collected. Here, in this context, we simply use the population of the origin area to approximate the productions and use the job of the destination area to approximate the attractions. Since the imputed travel volume share here is only used as a weighting factor of travel speed, such approximation, although not as accurate as what the travel demand forecasting procedure yields, should not yield any significant error.

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