Going Nowhere Fast: Urban Mobility, Job Access and Employment Outcomes

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Abstract

Providing fast transportation within cities is often considered as a way to improve labour market connections. This paper will quantify metropolitan level mobility with respect to home-work commuting. Commuter mobility in the US is found to vary substantially across metros in both levels and trends during the 2005-2014 study period. The impact of mobility on access to jobs is theoretically ambiguous due to mobility inducing urban sprawl. An instrumental variable method will exploit random variation in the political process governing transportation infrastructure funding. Results provide causal evidence that increased commuter mobility led workers to experience reduced local job density. Estimates fail to find evidence that commuter mobility improved labour market outcomes. Findings are consistent with increased commuter mobility exacerbating spatial mismatch through employment dispersion.

JEL: R23 R41 R42 R48 J64 J68

1 Introduction

Urban vehicle congestion is the topic of significant public concern. An annual report from the Texas Transportation Institute argues that the costs of congestion to the US economy are approximately $160 billion annually (Schrank et al., 2015). A typical policy response has been to construct infrastructure that allows commuters to move at faster speeds through urban environments, such as new highways or transit systems. If worker and firm locations are taken as exogenous, such projects may successfully reduce commute times. However, the higher order consequences of mobility, such as inducing urban sprawl, make the equilibrium consequences of transportation infrastructure on commute times unclear. Sprawl may act to increase the average distance between workers and firms, counteracting the benefits of mobility. This paper will analyse the relationship between urban mobility, sprawl and labour market connections. I first implement an explicit measure of mobility, attempting to capture the rate with which a commuter can traverse urban space. Subsequently, I test for a causal effect of mobility on sprawl and job accessibility across US metros. Finally, I test for a link between mobility and metropolitan labour market outcomes.

Though many authors have investigated the mechanics of vehicle congestion (Couture et al., 2018; Duranton and Turner, 2011; Meyer, 1959; Walters, 1961; Lindley, 1987), limited work has been undertaken to determine the broad impacts of urban mobility on economic or labour market outcomes. Prior investigations have attempted to connect congestion and economic growth, but unlike the current paper, do not explicitly consider mobility's propensity to induce urban sprawl. Boarnet (1997) was able to show a relationship between reductions in road congestion and economic growth across counties in California. However, Boarnet (1997) found no direct relationship between the expansion of road infrastructure and economic growth. Prud'homme and Lee (1999) investigated the impact of commuter speed on urban productivity. In the context of France, the study estimated that a 10% increase in urban transport speed was related to a 2.9% increase in city-wide productivity. The study stressed the necessity of limiting urban sprawl in order for these returns to be realized.

The literature has described potential negative consequences of high mobility urban environments, such as auto dependence and sprawl (Cervero, 1997; Crane, 2000; Grengs et al., 2010; Jacobs, 1961; Levine et al., 2012; Yang, 2008). Cervero (1997) questioned the wisdom of promoting urban mobility and suggested an increased focus on accessibility. Cervero (2001) investigated the impact of mobility and urban form on productivity in US metros, characterising the investigation as an attempt to contrast the economic consequences of “sprawl” versus “compact city” development. The research noted the endogenous relationship between economic growth and mobility, as high growth may spawn an increase in commuting trips, which increases congestion and reduces mobility.

Clear benefits exist in enabling residents to access a wider set of destinations and expend less time on travel. Kain (1968) provided the framework of spatial mismatch to explain why the inaccessibility of work locations may result in diminished employment outcomes, a theory expanded upon by numerous studies (Coulson et al., 2001; Gobillon et al., 2007; Holzer, 1991; Immergluck, 1998; Rogers, 1997; Smith and Zenou, 2003). The lagging job market performance amongst those groups experiencing exclusion from private vehicle mobility has been explored in the transportation mismatch literature (Baum, 2009; Gurley and Bruce, 2005; Kawabata, 2003; Ong and Miller, 2005; Taylor and Ong, 1995). A transportation network that accommodates the locating of employment opportunities at great distances from urban population centres puts workers with high transportation costs or low private vehicle access at a disadvantage through both truncating the set of spatially viable employment opportunities and increasing the costs of job search and commuting. Prior work has identified black (Zax and Kain, 1996) and youth (O’Regan and Quigley, 1996) populations to be particularly sensitive to spatial isolation from jobs.

Some research has attempted to directly estimate the causal effect of mobility on job accessibility. Grengs et al. (2010) examined accessibility in San Francisco and Washington, DC, and found that San Francisco allowed for higher vehicle speeds, while DC was oriented to accommodate shorter trips by distance. Levine et al. (2012) refined this theory, discussing how increases to mobility may fail to improve accessibility due to sprawl. Levine et al. (2012) tested the theory on 38 large metropolitan regions in the US, finding that high travel speeds related to reductions in job accessibility, consistent with a dynamic increase in sprawl overwhelming the intuitive accessibility benefits of mobility. Baum-Snow (2007) provided a seminal paper relating highway construction to sprawl, establishing that the construction of the US interstate highway system explains a significant portion of population decline in central cities through the mid 1900s. The current study will provide complementary empirical support to the findings of Baum-Snow (2007), examining a more recent time frame.

This paper will proceed as follows. Section 2 describes a metric for metropolitan mobility. Section 3 introduces data sources. Section 4 describes how mobility has changed through time in US metros. Section 5 shows theoretically how increased mobility could reduce the accessibility of jobs. Section 6 proposes an instrumental variable identification strategy. Section 7 presents results and Section 8 concludes.

2 Measuring Mobility

In order to study urban mobility empirically an objective measure of mobility must be applied. The proposed metric is adapted from Prud'homme and Lee (1999). The measure takes the existing built environment as an enabler of mobility and attempts to measure the speed with which an individual overcomes urban space. This study will be specifically concerned with home-work commuting.

Provided individual level observations such that an individual's residence and workplace can be geographically identified, it is possible to calculate the "as the crow flies" distance separating these two locations. Such a route follows a geodesic line. Commuters are limited to travelling through the built transportation network, forcing them to deviate from the geodesic. The level of commuter deviation from the geodesic is a function of the circuity of the transportation network (Levinson and El-Geneidy, 2009; Giacomin and Levinson, 2015). By using geodesic distance, the current paper will allow for variation in network circuity to impact the measure of mobility. The measurement of the geodesic line is therefore an intentional abstraction and is not meant to capture the actual route executed. The departure from network analysis to the conception of urban space as a continuous velocity field has some commonality with Angel and Hyman (1970).

The speed with which an urban resident navigates a given geodesic distance is a function of (1) the average ground speed with which they travel and (2) the extent to which the existing transportation network prompts the commuter to deviate from their ideal geodesic. Metropolitan conditions that enable high ground speeds and direct routes will enable higher mobility. The velocity with which a traveller can overcome the geodesic distance spanning their origin-destination pair will be referred to as commuter velocity. The commuter velocity of an individual is given simply by equation 1. Commuter velocity is distinct from more commonly applied mobility metrics derived from vehicle kilometres travelled (VKT) data, notably used in Couture et al. (2018) and Duranton and Turner (2011). Such metrics do not account for the role of route circuity. Figure 1 displays the correlation between the average "ground speed" of a commuter and this study's metric of commuter velocity. The ground distance between home and work is recovered from the 2009 National Household Travel Survey–the same survey used in Couture et al. (2018) as well as Duranton and Turner (2011). Only 47 large metros have sufficient data to calculate the statistic. The correlation between the two metrics is .44, suggesting the metrics are measuring unique variations in mobility.

$$\Omega_i = D_i \quad / \quad t_i \tag{1}$$

Where Ω_i is the commuter velocity of individual i, D_i is the geodesic distance between individual i's origin and destination pair, and t_i is the time taken to complete individual i's trip.

Taken over the entire workforce (N) of a region, commuter velocity (Ω) provides an indication of the regional level mobility provided by the transportation network (equation 2).

$$\Omega = \frac{\sum_{i=1}^{N} D_i}{\sum_{i=1}^{N} t_i} \tag{2}$$

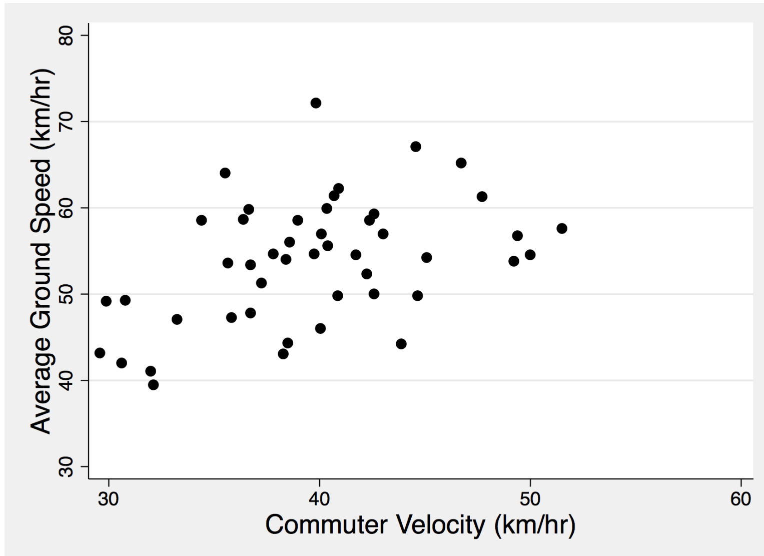
The remainder of this study will apply commuter velocity calculations to US metropolitan areas. Commuter velocity displays a high level of variability across US metropolitan areas and across US regions.

Transportation investment in the US has been historically dominated by the accommodation of private vehicles (Giuliano and Dargay, 2006; Grengs et al., 2010). Investment is normally directed towards either creating new roadways that provide more direct access to destinations, or building out existing roadways to accommodate more traffic at a higher speed. Therefore, much of transportation investment in the US can be characterized as an attempt to increase Ω. It is not clear that this is a desirable policy goal, given the secondary effects on urban sprawl discussed below.

3 Data

In order to calculate Ω the current study aggregates data from multiple sources. Consistent data from all sources are obtained for the period of 2005 through 2014, which comprises the period of study. US metropolitan Core Based Statistical Areas (CBSA) are used as the unit of analysis. CBSA boundaries are held consistent through time and conform to the 2010 Office of Management and Budget delineations. This paper makes use of the Longitudinal Employer-Household Dynamics (LEHD) data products, compiled by the US Census Bureau. The LEHD Origin-Destination Employment Statistics (LODES) data set provides located home-work pairs for employees across the US. Home and work locations are identified at the census block level, providing a high degree of locational precision. LEHD data records approximately 95% of wage and salary employment nationally, notable omissions are self-employed individuals and US military personnel

Figure 1: Correlation Between a Common Mobility Measure and Commuter Velocity (Ω)



(Graham et al., 2014). Any CBSA resident who works outside of their home CBSA is dropped from analysis, this applies to less than 1% of the sample. An additional limitation of the data is the exclusion of workers who live and work in different states. LODES contains incomplete data for the District of Columbia, 2005-2009; Massachusetts, 2005-2010; and Wyoming, 2014. Metro-year observations affected by these instances of missing data are omitted from analysis.

The LEHD assigns work locations according to the physical mailing address of the employer. This method may systematically misrepresent actual commuting patterns, particularly within industries that have inconsistent work locations, such as the construction industry (Graham et al., 2014). Misreported work locations could introduce bias in the estimation of commuter velocity. However, assuming these inaccuracies are consistent through time, this bias will generally cancel out in the identification strategy, which will rely on year-to-year variation in commuter velocity within a particular metro.

This paper will incorporate American Community Survey (ACS) data, which is also collected by the US Census Bureau. To identify trends through time, one-year estimates are used. The Public Use Microdata Sample (PUMS) provides annual individual level observations for a randomly selected 1% of the US population. Variables are taken directly from the Integrated Public Use Microdata Series data products (Ruggles et al., 2014). The ACS asks workers to report the number of minutes taken to commute one way to work, "door-to-door," which will be used as the measure of commute travel time. PUMS also contains a wide array of individual level demographic characteristics that will be used in analysis. 17 CBSAs lack ACS labour force data by race group for some or all years and are dropped from analysis. These 17 CBSAs are small, resulting in the ACS failing to survey a sufficient sample. The final sample includes 361 metropolitan CBSAs, of which 355 are available across all ten years.

Processed LODES and ACS data are collapsed to the CBSA level. PUMS observations are identified at the Public Use Micro Data Area (PUMA) and are crosswalked to CBSAs using the Missouri Census Data Center's Geographic Correspondence Engine. CBSA summary statistics are provided in Table 1. The combining of LODES and ACS data allows metropolitan mobility to be measured annually. This method captures richer variation through time than provided by alternative data sources for mobility, for instance the US National Household Travel Survey (NHTS), which is only conducted once every five to seven years and is only available for a subset of metropolitan areas .

Table 1: CBSA summary statistics

Variable	Mean	Std. Dev.
Commuter velocity (km/hour)	31.485	7.790
Employment rate	0.560	0.061
Labour force participation	0.605	0.057
Weekly hours worked	37.994	1.357
White	0.829	0.112
Black	0.092	0.096
Hispanic	0.090	0.129
High school completion	0.862	0.053
College completion	0.259	0.080
Graduate school completion	0.098	0.040
Mean age	47.598	2.628
Population	703,464	1,598,416
Metropolitan GDP (millions)	35,959	100,666
N	3,585	

Data for the instrumental variables on congressional representation are collected from publicly available directories of the US House of Representatives standing committees. I manually digitized these directories. Highway Trust Fund allocations to states are publicly available from the Federal Highway Administration Office of Highway Policy Information. Data for metropolitan level GDP controls are gathered from the US Department of Commerce, Bureau of Economic Analysis.

4 A Recent History of Commuter Velocity

In 2014, the commuter velocity (Ω) of the average US commuter was 36.4 km/hr. There exists significant variation across US Census regions. In 2014, commuter velocity in the South averaged 39.4 km/hr, but in the Northeast was only 30.5 km/hr. Commuters in the Midwest and West regions travelled at 37.0 km/hr and 35.8 km/hr respectively (Figure 2A).

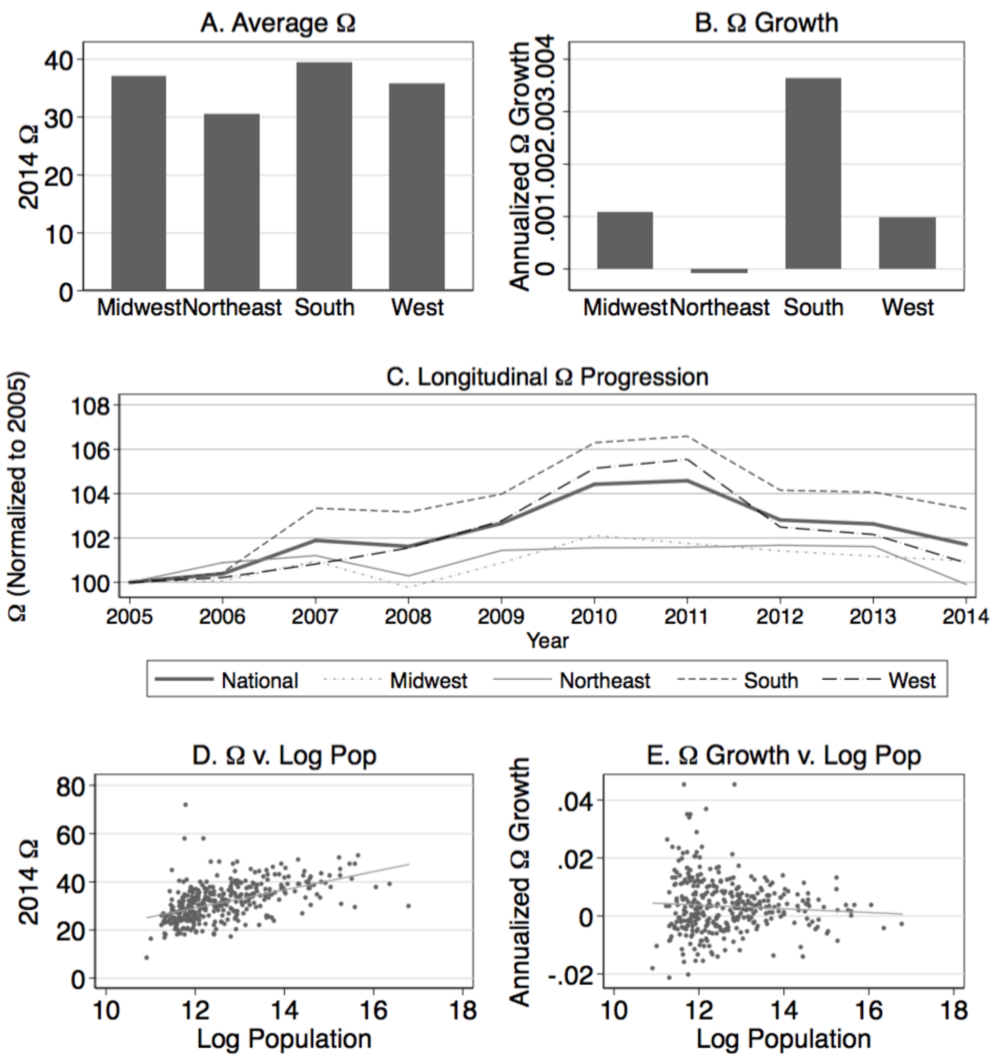


Figure 2: Summary of commuter velocity.
Annual growth rates are taken over 2005-2014. Figures A-C are weighted by CBSA population. Figures D-E display individual metros. Ω is commuter velocity measured in km/hour.

Between 2005 and 2014, growth in commuter velocity was highest in the South where residents experienced an annualized growth rate of 0.36% (Figure 2B). The Midwest and West experienced annualized growth rates of 0.11% and 0.10% respectively. The Northeast experienced essentially no change in commuter velocity between 2005 and 2014. The period of study encompasses a sustained period of national growth in average commuter velocity from 35.8 km/hr in 2005 to 37.4 km/hr in 2011, followed by a decline to the 2014 value of 36.4 km/hr (Figure 2C). Commuter velocity trends roughly mirror contemporaneous job growth patterns in the US, consistent with literature demonstrating declining mobility during times of employment growth (Morrison and Lawell, 2016).

Larger metros have higher commuter velocity values on average. For every 100,000 person increase in population, Ω was 0.13 km/hr higher on average in 2014 (Figure 2D). Population is able to explain 7% of the variation in commuter velocity. There is no clear relationship between metro size and commuter velocity growth over the period of study (Figure 2E).

Table 2 provides a list of 2014 commuter velocity values for all CBSAs with a population over one million. The highest commuter velocity values occur in metros that are notoriously highway and automobile dependent. Dallas had the highest commuter velocity amongst large cities in 2014 at 50.6 km/hr, followed by Phoenix at 50.0 km/hr. Nashville, Houston and Atlanta were also among the fastest five large cities. San Jose had the slowest commuter velocity amongst large cities at 26.7 km/hr. Giacomin and Levinson (2015) found San Jose's road network to be amongst the most circuitous in the US. San Jose also experienced a significant decline in commuter velocity over the study period (-1.1% per year), consistent with very high local job growth contributing to congestion. New York City, which is often cited for its high vehicle congestion, had the third lowest commuter velocity amongst large metros at 29.7 km/hr.

5 Commuter Velocity has an Ambiguous Effect on Job Access

To establish that commuter velocity (Ω) could theoretically raise or lower job accessibility I present a simplified model. For this section, I assume a worker is located on a flat, featureless plain such that commute velocity is equal in all directions and jobs are distributed uniformly. In this environment, the area accessible to a worker will be equal to the area of a circle with a radius matching the distance the worker can travel in time τ. τ is set exogenously and corresponds to the maximum time a worker is willing to spend in commute. The density of jobs on the flat, featureless plain is some positive number ζ. Equation 3 captures the quantity of jobs accessible to a worker.

$$J_i = \pi(\Omega\tau)^2\zeta \tag{3}$$

Where J_i is the number of jobs accessible to worker i within time τ and ζ is the density of jobs.

Table 2: Large Metropolitan Areas (>1,000,000), by 2014 Commuter Velocity (Ω)

Rank*	CBSA name	Ω	Annualized growth in Ω, 05-14	Avg km	Avg time
4	Dallas-Fort Worth-Arlington, TX	50.6	0.4	23.3	27.6
5	Phoenix-Mesa-Scottsdale, AZ	50.0	1.3	21.6	25.9
6	Nashville-Davidson–Murfreesboro–Franklin, TN	49.0	0.3	21.9	26.8
10	Houston-The Woodlands-Sugar Land, TX	47.4	0.0	23.4	29.7
12	Atlanta-Sandy Springs-Roswell, GA	47.2	0.4	24.7	31.4
13	Birmingham-Hoover, AL	47.0	0.6	20.3	25.9
15	Oklahoma City, OK	45.4	0.9	16.8	22.2
17	Detroit-Warren-Dearborn, MI	45.0	0.2	20.3	27.1
21	Columbus, OH	44.1	-1.4	17.0	23.1
24	St. Louis, MO-IL	43.1	0.5	18.2	25.4
27	Rochester, NY	42.7	0.4	15.0	21.2
28	Indianapolis-Carmel-Anderson, IN	42.5	0.5	17.7	24.9
29	Riverside-San Bernardino-Ontario, CA	42.4	0.9	22.5	31.8
30	Minneapolis-St. Paul-Bloomington, MN-WI	42.3	-0.6	17.9	25.4
33	Charlotte-Concord-Gastonia, NC-SC	41.9	0.3	18.3	26.2
34	Jacksonville, FL	41.8	0.8	17.9	25.7
35	Richmond, VA	41.4	0.7	17.2	25.0
37	Miami-Fort Lauderdale-West Palm Beach, FL	41.1	0.2	19.6	28.5
38	San Antonio-New Braunfels, TX	40.9	0.5	17.4	25.6
46	Kansas City, MO-KS	39.9	0.1	15.5	23.4
51	Tampa-St. Petersburg-Clearwater, FL	39.6	-0.1	17.8	27.0
53	Cleveland-Elyria, OH	39.4	0.4	15.9	24.2
54	San Diego-Carlsbad, CA	39.3	0.3	16.7	25.5
58	Virginia Beach-Norfolk-Newport News, VA-NC	39.1	0.7	15.5	23.8
60	Austin-Round Rock, TX	39.0	0.2	17.2	26.4
62	Los Angeles-Long Beach-Anaheim, CA	38.8	-0.4	19.3	29.8
64	Memphis, TN-MS-AR	38.7	0.4	15.4	23.8
67	Raleigh, NC	38.4	0.0	16.3	25.6
68	Pittsburgh, PA	38.2	-0.2	17.2	26.9
70	Sacramento–Roseville–Arden-Arcade, CA	38.1	0.4	16.8	26.5
73	Chicago-Naperville-Elgin, IL-IN-WI	37.7	0.4	20.0	31.8
76	Seattle-Tacoma-Bellevue, WA	37.5	-0.6	18.6	29.8
79	Buffalo-Cheektowaga-Niagara Falls, NY	37.3	0.6	13.0	21.0
83	New Orleans-Metairie, LA	37.1	1.4	15.6	25.2
84	Orlando-Kissimmee-Sanford, FL	37.0	0.8	17.1	27.7
85	Cincinnati, OH-KY-IN	37.0	-0.1	15.2	24.6
96	Milwaukee-Waukesha-West Allis, WI	36.0	-0.3	14.1	23.4
103	Hartford-West Hartford-East Hartford, CT	35.7	0.0	14.0	23.5
115	Louisville/Jefferson County, KY-IN	34.9	0.1	14.0	24.0
127	Denver-Aurora-Lakewood, CO	34.5	-0.5	15.8	27.6
151	Baltimore-Columbia-Towson, MD	33.2	-0.4	16.7	30.2
153	Las Vegas-Henderson-Paradise, NV	33.1	1.1	13.5	24.5
162	Salt Lake City, UT	32.2	0.1	12.1	22.5
193	San Francisco-Oakland-Hayward, CA	30.7	-0.9	16.4	32.2
199	Portland-Vancouver-Hillsboro, OR-WA	30.2	-0.3	13.0	25.9
206	New York-Newark-Jersey City, NY-NJ-PA	29.7	-0.3	17.8	36.0
217	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	29.1	0.1	14.2	29.3
252	San Jose-Sunnyvale-Santa Clara, CA	26.7	-1.1	12.3	27.5

*Rank indicates the CBSA's commuter velocity (Ω) ranking amongst the full set of 359 CBSAs for which there is 2014 data. Avg km is the average geodesic distance covered by a one-way commute. Avg time is the average number of minutes elapsed during a one-way commute.

For a static city, in which workers and firms do not move in response to changes in Ω, any increase in Ω increases the number of accessible jobs to the worker. Equation 4 captures the partial effect of a change in Ω on job accessibility in a static city. The partial derivative is strictly positive.

$$\frac{\partial J_i}{\partial \Omega} = 2\pi\Omega\tau^2\zeta \tag{4}$$

Equation 5 considers the case in which ζ is a function of Ω; wherein local firm density around a worker responds to changes in mobility. For example, an increase in Ω might reduce the density of jobs by encouraging urban sprawl.

$$\frac{\partial J_i}{\partial \Omega} = \underbrace{2\pi\Omega\tau^2\zeta}_{\text{Static Effect} > 0} + \underbrace{\pi(\Omega\tau)^2\frac{\partial \zeta}{\partial \Omega}}_{\text{Dynamic Effect} < 0} \tag{5}$$

In equation 5, the first term of the derivative is identical to the partial derivative in the static case and takes a positive value. If firms alter locational decisions in response to increases in Ω such that local job density decreases (i.e. $\frac{\partial \zeta}{\partial \Omega} < 0$) the second term of Equation 5 will be negative and depending on the magnitude of $\frac{\partial \zeta}{\partial \Omega}$, $\frac{\partial J_i}{\partial \Omega}$ may be negative.

Equation 6 identifies a critical inequality of the partial effect of mobility on sprawl ($\frac{\partial \zeta}{\partial \Omega}$). When Equation 6 holds, a marginal increase in Ω will lead to a decrease in the number of accessible jobs.

$$\frac{\partial \zeta}{\partial \Omega} > \frac{-2\zeta}{\Omega} \tag{6}$$

This toy model illustrates why the effect of mobility (Ω) on accessibility is theoretically ambiguous: if mobility's impact on locational dispersion is sufficiently large in magnitude, the net impact of increased mobility will be a decline in accessibility. Equation 6 is a codification of the central question of Levine et al. (2012): whether access requires density or speed.

Figure 3 decomposes equation 5 into the static and dynamic effects. Although the parameters are in general unobserved, reasonable values can be estimated from data and are used in Figure 3. A sufficiently strong job density effect breaks the equation 6 threshold and leads to a negative partial effect of commuter velocity on accessibility.

The proposed model has notable limitations. The assumption of uniformly distributed jobs is incompatible with the monocentric city model. Modelling ζ as a decreasing function of distance to the city centre would increase realism, though complicate derivations. Additionally, an exogenously assumed limit to commute time (τ) is restrictive. A more complex model might consider τ to be determined endogenously, or as a transport cost

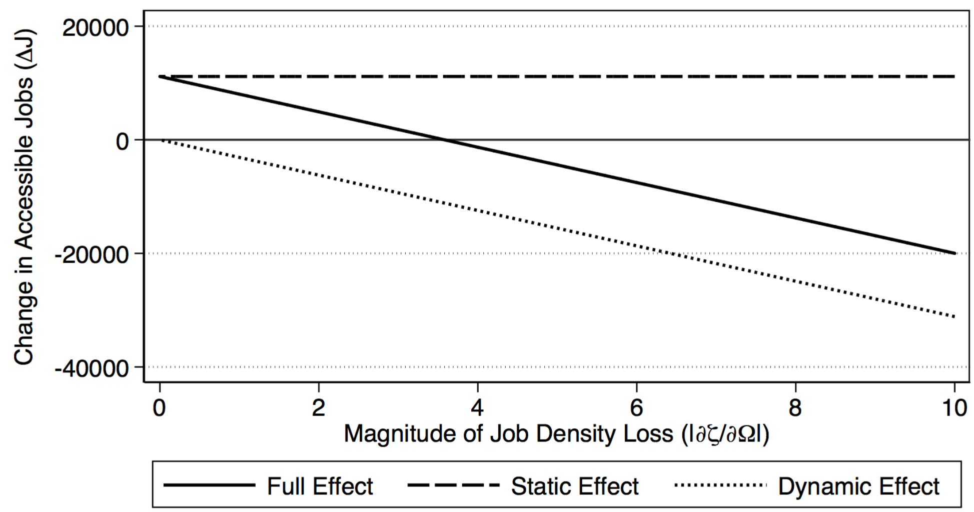


Figure 3: Partial effect of increase in commuter velocity on job accessibility, dynamic city. Parameterization: $\tau = 1$ hour, $\zeta = 56.3\frac{\text{jobs}}{\text{km}^2}$, $\Omega = 31.5\frac{\text{km}}{\text{hour}}$. τ is set according to the 95^{th} percentile of commute duration observed in micro ACS data. ζ is set according to the average density of jobs within a 30 km radius of a worker according to LEHD data. Ω is set according to the average CBSA-year observation. In this parametrization, if job density falls by more than 3.6 jobs per km^2 for every 1km/h increase in Ω, a rise in Ω reduces job access.

that causes the probability of employment to be decreasing in τ.

6 Identification Strategy

Inferring a causal relationship between mobility, labour market access and labour market outcomes must overcome two major econometric hurdles. Firstly, omitted variable bias is likely to confound analysis. Idiosyncratic characteristics of metros may simultaneously influence both labour market performance and the travel behaviour of workers. For example, very dense cities might be both slow and productive. Several papers are able to explain travel behaviour through observed metro characteristics (see, for example Cervero and Kockelman (1997); Schwanen and Mokhtarian (2005)). Although some metropolitan characteristics can be directly controlled for, some remain unobserved. The current study overcomes this barrier by leveraging the panel format of the data. Omitted variable bias can be handled by including metropolitan level fixed effects in all regressions, and basing estimation on variation that occurs within metros, across years. Additionally, year fixed effects are included to account for national economic changes across years. The basic regression model is represented by equation 7.

$$K_{mt} = \beta_0 + \beta_1 \Omega_{mt} + X_{mt} + F_m + Y_t + \epsilon_{mt} \tag{7}$$

Where K_{mt} is a labour market outcome of interest for metro m in year t, Ω_{mt} is the commuter velocity of metro m in year t, X_{mt} is a vector of metro-year specific demographic and economic controls (mean age, white population share, black population share, Hispanic population share, high school completion rate, college completion rate, graduate degree completion rate and log of metropolitan GDP), F_m is a vector of metro dummy variables and Y_t is a vector of year dummy variables.

A second barrier to identification arises due to the possibility that labour market changes through time and changes in observed mobility are endogenous (Morrison and Lawell, 2016). Labour market growth may generate congestion, which lowers mobility. Conversely, a labour market contraction may free up transportation infrastructure, which could lessen congestion and increase mobility. The current study seeks to estimate the effect of mobility on labour outcomes, and must therefore remove the effects of reverse causation. Identification is achieved through the use of instrumental variables.

To be valid, the chosen instrument must influence the endogenous variable (mobility), but cannot wield influence on the dependent variable (labour market outcome) other than through mobility. The proposed instrument is lagged political representation on the US House of Representatives Transportation and Infrastructure standing committee, an approach successfully implemented in Knight (2002).

A congressperson being appointed to the committee is a result of a political process which is plausibly orthogonal to future economic conditions of the state, as argued in Knight (2002). Committee members possess outsized power to influence the allocation of earmarked transportation spending, and have political incentives to direct funding towards the state of their constituents. Investment in transportation infrastructure has an intuitive relationship with commuter velocity. Firstly, building new roadways may lower the circuity of particular routes. Secondly, improving road conditions or capacity may increase ground speed. Thirdly, new infrastructure may prompt mode switching as commuters shift to improved modes. The dominance of private vehicle transportation in the US suggests that mode choice is a secondary issue for all but a few large metros in which public transit is a common alternative.

The US Department of Transportation (DOT) allocates state transportation funds in accordance with acts of the US Congress. The formula for allocation is complex, and includes many so-called bonuses to particular states. The political process is such that the federally controlled DOT has power to allocate money to states, while recipient states subsequently have significant discretion regarding where these funds are spent within state boundaries. The complexities of allocation have led to criticisms of the apparent arbitrary and politically capricious nature of allocations "that have little or nothing to do with a state's transportation needs" (Cooper and Griffith, 2012). Much of the variation in fund allocation between states is a function of state size, in terms of population, geography and economic activity. However, year-to-year variation in funding is considerable, and is primarily the result of political negotiations, which largely take place within the Transportation and Infrastructure Committee.

Knight (2002) investigated whether federal highway grants crowd out state infrastructure spending, arguing that OLS regressions of state transportation spending on federal grant amounts will be biased, as federal grants are endogenous to local demand for infrastructure. Knight (2002) implemented cross-state variations in congressional committee representation as instruments for federal grants. The key identifying assumption is that while grants may be endogenous to economic conditions, the political happenstance that leads to particular committee appointments is orthogonal to state economic conditions. Under instrumentation, Knight (2002) found crowd out estimates were substantially reduced.

For the current analysis, the lagged number of congress members a metro's "home state" has appointed to the Congressional Transportation and Infrastructure Committee will serve as the instrument for commuter velocity. In cases where a CBSA spans multiple states, the state in which the highest portion of the CBSA population resides is considered as the home state. Within a lagged sample period (2002-2011), the average metro was represented by 2.32 "home state" congresspeople on the committee, with a standard deviation of 1.84 and a range of 0-7.

Due to the inclusion of metropolitan fixed effects, the variation preserved in the instrument represents the year-to-year vagaries in committee representation, independent of persistent state effects. If exogenous variation is in fact coming from arbitrary fluctuations in a state's political clout over funding legislation there should be a measurable effect of committee representation on allocations. The amount of federal highway trust fund money allocated to a metro's home state is regressed against contemporaneous committee representation, with standard fixed effects and controls. Having one additional congressperson on the committee relates to a highly statistically significant increase in federal highway trust fund allocations of $23 million to the home state (Table 3). Converting the regression to a log-level form yields the estimate that each additional congressperson increases allocations to the state by 0.7%.

Though it is clear that the instruments must be lagged so that mobility and land use conditions may respond to the shock, it is unclear what magnitude of lag is appropriate. The marginal changes in federal funding resulting from the instrument are likely insufficient

Table 3: Effect of Committee Representation on Home State Allocations, 2005-2015

	Funding (million $)	Log of Funding (million $)
	(1)	(2)
Committee Reps	23.03**	.007*
	(4.41)	(.003)
CBSA fixed effects?	Y	Y
Obs.	445	445

Significance levels: $*$: 5% $**$: 1%. Standard errors shown in parenthesis are clustered at the CBSA level. Each regression includes standard controls and fixed effects for CBSA and year.

to spur entirely new infrastructure projects. Rather, the mechanism proposed is that the additional funding allows for planned projects to be completed more quickly, or for small scale projects to be implemented, for example repavings or the addition of new lanes.

Table 4 provides first stage results for the IV analysis. The estimated partial effect of committee representation on commuter velocity is estimated for a range of lags. A three year lag is statistically significant, while two, four and five year lags are positive but fall short of significance. The largest effect for congressional representation is a three year lag, for which an increase in one committee member produces a 0.144 km/hr increase in Ω. To take advantage of the predictive power of each instrument, and to allow flexibility in the dynamics of how political representation affects mobility, multiple lags are used simultaneously in the first stage. Table 4, column 5 displays the first stage regression that will be used in subsequent analysis. The instruments are highly jointly significant. The joint F-statistic reported for the first stage regression rejects the null hypothesis that weak instrument bias is more than 10% of the bias existing in OLS estimates (Stock and Yogo, 2005). Using multiple instrument lags simultaneously allows for the implementation of an overidentification test. The Sargan-Hansen statistic fails to reject instrument validity across main model specifications. As a robustness check, I repeat all IV analysis using only the three year lagged instrument (shown in column 2), results are essentially unchanged under this alternative specification.

A significant first stage may at first seem at odds with Duranton and Turner (2011), which found the construction of new road infrastructure in US cities to have no impact on road congestion. However, the effect of road space on congestion is not being tested in this regression. Vehicle crowding on road space may remain, while Ω may increase through changes in commuter mode choice or lowered route circuity. This highlights an advantage of using commuter velocity (Ω), as the measure can capture all sources of increased urban travel speed.

A potential obstacle to the IV strategy is that additional highway funding to particular states represents a direct economic contribution through construction

Table 4: First stage regressions, predicting commuter velocity from lagged committee representation

	Outcome: Commuter Velocity				
	(1)	(2)	(3)	(4)	(5)
Committee Reps: 2 year lag	.093				.018
	(.059)				(.057)
Committee Reps: 3 year lag		.144**			.121**
		(.055)			(.044)
Committee Reps: 4 year lag			.104		.010
			(.054)		(.057)
Committee Reps: 5 year lag				.069	.026
				(.048)	(.052)
Obs.	3585	3585	3585	3585	3585
F-test for Joint Sig. of Instruments					9.41

Significance levels: * : 5% ** : 1%. Standard errors shown in parenthesis are clustered at the CBSA level. Each regression includes standard controls and fixed effects for CBSA and year.

employment and related local economic activity (Melo et al., 2013), this would undermine the instrument's exclusion restriction and bias estimation. However, this concern is tempered by a number of factors. Firstly, the partial effect of the instrument on annual funding ($23 million per congressperson) is small relative to a state economy. Secondly, lagging the instruments should insulate results from direct stimulus effects. Finally, annual metropolitan GDP is controlled throughout, which should absorb direct stimulus effects.

Instrumentation offers the additional important benefit of overcoming attenuation bias. Year-to-year variation in Ω is generally small, and a significant portion of this variation is likely measurement error. By relying on predicted Ω through the instruments, rather than observed Ω, the potentially biasing effects of measurement error are removed. Main results will be consistent with instrumentation undoing attenuation bias occurring in OLS regressions.

7 Results

7.1 Commuter Velocity as a Cause of Sprawl

The ambiguity of mobility's impact on employment access is a consequence of the potential for mobility to increase the spatial dispersion of employment relative to workers. This section will empirically test for a relationship between commuter velocity (Ω) and local job density (ζ). The precise spatial identification of workers and firms in the LEHD data allows for the local density of jobs to be calculated for individual workers, and subsequently averaged across a CBSA's workforce.

Table 5 regresses the density of local jobs (ζ) that surround a metro's average worker within various geodesic radii on commuter velocity (Ω), including CBSA and year fixed effects as well as CBSA-year demographic controls as detailed in section 6. OLS estimation suggests that increased Ω is related to a significant decrease in local job density across a range of search radii. Setting the commute radius to 30 km yields the result that a 1 km/hr increase in Ω relates to a drop in the density of jobs around the average worker of 0.26 jobs/km^2. Turning to IV estimation, the magnitude of the estimated effects increase substantially. Under instrumentation, the estimated partial effect evaluated for a 30 km commute radius is a drop of 3.74 jobs/km^2. The average metro in the sample provides its average worker access to 56.3 jobs/km^2 within a 30 km radius. The direction of results are robust to the choice of search radius. The magnitude of results are decreasing in the search radius, as larger radii lead to the inclusion of comparatively more undeveloped peripheral land. Regarding the relevant search radius, a worker willing to commute no more than 1 hour ($\tau = 1$) and whose metro offers the sample average commuter velocity (31 km/hr), will have an implied search radius of 31 km.

The -3.74 jobs/km^2 estimate in column 4 is very close to the -3.6 jobs/km^2 identified as the approximate threshold at which an increase in commuter velocity leads to a decrease in job accessibility (Figure 3). This back of the envelope calculation is suggestive evidence that the effect of Ω on job access is roughly zero, with the sprawl effects offsetting the mobility effects.

Table 5: Impact of commuter velocity (Ω) on mean localised job density (ζ)

	5km	10km	20km	30km	40km	50km	60km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Outcome: Mean Localised Job Density						
	Estimation Method: IV						
Commuter Velocity	-12.114	-8.695	-5.724*	-3.744*	-2.482*	-1.723*	-1.255*
	(7.081)	(4.763)	(2.671)	(1.711)	(1.166)	(.826)	(.610)
	Estimation Method: OLS						
Commuter Velocity	-2.231**	-1.349**	-.527**	-.255**	-.137**	-.080*	-.051*
	(.332)	(.226)	(.130)	(.081)	(.050)	(.032)	(.022)
Obs.	3585	3585	3585	3585	3585	3585	3585

Significance levels: $*$: 5% $**$: 1%. Standard errors shown in parenthesis are clustered at the CBSA level. Each regression includes standard controls and fixed effects for CBSA and year.

As a robustness check, a second metric for job access is tested. I calculate the average distance between a random worker and a random job for each metro. To calculate this metric, a geodesic distance matrix is constructed for census tract pairs within each CBSA. Within CBSAs in 2014, the average distance between a randomly selected worker and a randomly selected job was 27.4 km. Repeating the IV regression procedure on this outcome

Table 6: Impact of commuter velocity (Ω) on average distance to a job

	IV	OLS
	(1)	(2)
Commuter Velocity	.289*	.167**
	(.145)	(.046)
Obs.	3585	3585

Significance levels: $*$: 5% $**$: 1%. Standard errors shown in parenthesis are clustered at the CBSA level. Each regression includes standard controls and fixed effects for CBSA and year.

variable indicates a 1 km/hr increase in commuter velocity results in a 0.29 km increase in the average worker-job distance, significant at the 5% level (Table 6). The corresponding OLS estimate is 0.167 km, significant at the 1% level. These results provide further evidence that increases in Ω cause a dispersion of jobs relative to workers.

7.2 Labour Market Impacts of Commuter Mobility

This section will test for an effect of changing urban mobility on three metropolitan labour market outcomes: the employment rate, the labour force participation rate, and the average working hours per week amongst employed workers. Differential subgroup effects will be investigated.

Success in the labour market is related to the accessibility of jobs. Improvements in mobility could improve labour market outcomes through its effect on easing job search (Zenou, 2009) or causing a reduction in commuting costs (Hu, 2015). The previous subsection suggested the accessibility benefits of mobility may be counteracted by induced urban sprawl.

Table 7, panel A presents regression results of the effect of commuter velocity on the metropolitan employment rate. Under OLS, the effect of a 1 km/hr increase in Ω is a reduction in the employment rate of 0.2 percentage points. For reasons discussed above, OLS may suffer from endogeneity and attenuation bias. Under instrumentation of Ω, the effect is estimated to be -0.9 percentage points, though the result is statistically insignificant.

Adverse labour market outcomes across a metropolitan area are consistent with spatial and transportation mismatch literature which suggests that the expansion of high mobility policy leads to a decline in the ability of some workers to access and secure employment. Prior research suggests the groups most likely to suffer adverse labour market outcomes include nonwhite workers, youth, low skill workers, and workers without access to a private vehicle (Ihlanfeldt and Sjoquist, 1990; Kain, 1968; Kawabata and Shen, 2007; Tyndall, 2017; O'Regan and Quigley, 1998).

Table 7: Effect of commuter velocity on labour market outcomes

	All	White	College	No College	Car	Youth
	(1)	(2)	(3)	(4)	(5)	(6)
A.	**Outcome: Employment Rate**					
	Estimation Method: IV					
Commuter Velocity	-.009	-.005	.009	-.013	-.004	-.045*
	(.006)	(.005)	(.006)	(.007)	(.004)	(.020)
	Estimation Method: OLS					
Commuter Velocity	-.002**	-.002**	-.001*	-.002**	-.001**	-.002
	(.0003)	(.0004)	(.0005)	(.0003)	(.0002)	(.001)
Employment Rate (mean)	0.560	0.567	0.701	0.521	0.593	0.515
B.	**Outcome: Labour Force Participation Rate**					
	Estimation Method: IV					
Commuter Velocity	.005	.007	.015*	.003	.010*	-.022
	(.005)	(.005)	(.008)	(.005)	(.005)	(.012)
	Estimation Method: OLS					
Commuter Velocity	-.001**	-.001**	-.001	-.001**	-.0004*	-.001
	(.0002)	(.0002)	(.0004)	(.0003)	(.0002)	(.0005)
Labour Force Partic. (mean)	0.605	0.608	0.724	0.573	0.638	0.611
C.	**Outcome: Weekly Hours Worked**					
	Estimation Method: IV					
Commuter Velocity	-.375*	-.392*	-.194	-.451*	-.263	-1.171*
	(.187)	(.191)	(.180)	(.217)	(.146)	(.530)
	Estimation Method: OLS					
Commuter Velocity	-.043**	-.053**	-.008	-.054**	-.039**	-.050**
	(.009)	(.010)	(.011)	(.010)	(.006)	(.019)
Hours Worked (mean)	37.99	38.16	40.63	36.99	38.30	30.63
Obs.	3585	3585	3585	3585	3585	3585

Significance levels: $*$: 5% $**$: 1%.
Standard errors shown in parenthesis are clustered at the CBSA level.
Each regression includes standard controls and fixed effects for CBSA and year.

Panel A, columns 2-6 estimate employment effects by demographic subgroup. The estimated partial effect of Ω on the employment rate of the non-college educated, and youth are lower than the aggregate estimate. I find that the negative effects of commuter mobility on white workers, the college educated and workers with access to a private vehicle are all higher the aggregate estimate. In fact, I find the employment rate of those with a college education increases by 0.9 percentage points per unit increase in Ω. Youth workers stand out for having particularly adverse reactions to increases in mobility conditions.

Table 7, panel B shows the results for labour force participation, an IV regression for the full sample suggests a statistically insignificant 0.5 percentage point increase in labour force participation per km/hr increase in Ω. However, division of the labour force into subgroups reveals interesting heterogeneity. White workers, the college educated and those with access to a private vehicle experience larger increases in labour force participation than the aggregate estimate. Noncollege educated workers and youth are more adversely affected. Youth cohorts actually experience a decrease in labour force participation as a result of rising commuter velocity.

Examining the effect of commuter velocity on hours worked amongst employed workers allows for the estimation of mobility's effect on the intensive margin of labour supply. Variable spatial access to place of work may impact the number of hours supplied per week, through the effect on commuting costs. Table 7, panel C provides estimated effects. Amongst the full sample IV regression (column 1), a 1 km/hr increase in Ω corresponds to a significant reduction in labour supplied of 23 minutes per week. Examination by subgroup reveals familiar patterns. Youth are once again disproportionately negatively affected. The large effect amongst youth may be reflective of a high share of youth holding part time jobs with adjustable hours. A pronounced effect on youth is consistent with the findings of O'Regan and Quigley (1991, 1996, 1998).

90.1% of ACS respondents have access to a private vehicle. Those with a private vehicle fare better in response to an increase in mobility. Findings are suggestive of an overarching mechanism: expansion of high mobility policy is harmful to individuals who are not able to fully participate in the upside of high mobility infrastructure, while being exposed to the downside burden of employment sprawl.

8 Conclusion

US cities differ widely in how quickly workers can move through urban space. The impact of mobility on employment accessibility can be considered through two channels. First, rapid movement extends the area that is accessible to commuters, improving access. Second, mobility enables sprawl, which reduces the spatial density of jobs. This paper provides a direct estimate of the causal effect of mobility on sprawl and metropolitan labour market outcomes, unique to prior literature. I present significant evidence linking increased mobility to urban sprawl. I find no evidence that mobility increases overall labour market outcomes, but I do find evidence that increased mobility exacerbates inequalities in labour market outcomes, with downside effects concentrated amongst nonwhite workers, less educated workers and youth. Policy and infrastructure investment that seek to aid labour markets through reducing vehicle congestion or otherwise increasing the mobility of commuters may be self defeating due to endogenous sprawl.

Spatial and transportation mismatch literature provide viable theory to understand why high urban mobility may bring about negative job market consequences for particular populations. Future research should investigate heterogeneous effects more deeply through use of individual level micro data.

The near future prospect of autonomous vehicles may enable a further increase in commuter mobility. Compounding the effect, the mobility benefits of autonomous vehicles may initially accrue to an affluent minority while resultant urban spatial dispersion would affect the wider population. Understanding how increases in mobility generate urban sprawl is therefore likely a topic of continued interest.

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