Effects of Road and Other Mode Supply on Car Use

Maria Börjesson*1,2, Pernilla Ivehammar[2]

1 VTI Swedish National Road and Transport Research Institute, Sweden

2 Department of Management and Engineering (IEI), Linköping University, Sweden

SHORT SUMMARY

This paper estimates how changes in road supply, non-car mode supply, and destination density affect individuals' vehicle kilometres travelled (VKT). Using population-wide Swedish register panel data for 1998, 2005, and 2017 matched to historically reconstructed transport networks and simulated generalized travel times, we construct logsum-based accessibility measures by mode. Methodologically, we combine long-horizon first-difference models with an instrumental-variable strategy based on accessibility changes around the initial residential zone to address spatial sorting and time-varying endogeneity. We show that pooled cross-sectional models substantially overstate behavioural responses relative to first-difference and IV estimates. The most robust result is a modest reduction in VKT from improvements in non-car accessibility, while direct effects of road supply and density become small once sorting is accounted for. Improved non-car accessibility modestly reduces VKT: a one-standard-deviation increase in relative accessibility lowers car use by 1–3.5%.

Keywords: Demand management; Vehicle kilometres travelled (VKT); Logsum; Non-car transport modes; Residential self-selection; Panel data

1. INTRODUCTION

Reducing traffic volumes is an important complement to vehicle decarbonization. While carbon pricing is a cost-effective instrument for curbing driving, higher user prices are often politically contested and raise concerns about affordability, equity, and accessibility. This motivates interest in demand-management strategies that reduce car travel by improving non-car alternatives, shaping land use to support shorter trips and mode shift, and reallocating investment away from road expansion, rather than by directly increasing the pecuniary cost of driving. Yet much of the empirical literature estimating how road capacity, transit supply, and land-use density affect car travel relies on cross-sectional variation. Such comparisons are vulnerable to residential self-selection and spatial sorting: individuals with stronger preferences for driving tend to locate in areas with higher car accessibility, while individuals with stronger preferences for public transport or active modes tend to locate in denser areas with better non-car accessibility (Mokhtarian and Cao, 2008; Cao et al., 2007). Studies using temporal variation (e.g., Duranton and Turner, 2011) partly address these concerns, but MSA-level panels remain vulnerable to endogeneity. Both road and transit expansions can be a policy response to congestion and rising VKT (reverse causality), and common demand shocks (e.g., population and employment growth) may simultaneously increase VKT and trigger road (and transit) expansions (Cervero and Hansen, 2002; Fulton et al., 2000).

This short paper focuses on the methodology developed to address these challenges. We combine (i) logsum-based, mode-specific accessibility measures constructed from simulated generalized travel times and destination opportunities (Ben-Akiva and Lerman, 1985), (ii) individual-level first-difference models that purge time-invariant unobserved heterogeneity correlated with location, and (iii) an instrumental-variable strategy that isolates plausibly exogenous accessibility changes driven by developments around the individual's initial residential zone. We apply the approach to population-wide Swedish register data for 1998, 2005, and 2017, and quantify how conventional pooled cross-sectional models overstate behavioural responses relative to longitudinal designs.

2. METHODOLOGY

We use linked Swedish register microdata for all adults in mid-Sweden (approximately four million residents), including geocoded home locations and annual VKT from odometer readings at mandatory vehicle inspections. We construct two balanced panels, 1998–2005 and 2005–2017, and restrict the sample to individuals aged 25–81.

Accessibility depends on both the attractiveness of the destination and the generalized travel cost to get there. The generalized travel times for all origin-destination zone pairs are simulated using the National Transport Model. In this model, origins and destinations are defined as zones. Each zone is connected to the main transport network via a geographic point called the centroid. Using the coordinates of the centroids and individuals' residential locations from the registry data, each individual is assigned to the nearest centroid. All jobs (in the third database) are assigned to their nearest centroid. We measure the attractiveness of each destination zone as the number of jobs in the zone (which should reflect the attractiveness for most trip purposes).

The transport model uses historical data on population and transport systems from 1998, 2005, and 2017, including infrastructure for both road and transit (including rail). This allows us to simulate generalized travel times for each of these three years.

We compute generalized travel times between zone centroids for car, public transport, walking, and cycling using historically reconstructed transport networks and the national transport model for each year. Destination attractiveness is measured by jobs at destinations. For each mode, we aggregate generalized costs and destination opportunities into logsum accessibility measures, which are directly interpretable within discrete-choice travel demand models.

We measure accessibility using a logsum formulation that covers four modes: car (c), public transit (p), walking (w), and cycling (b). Accessibility is calculated based on generalized transport costs between zones. All residents of zone r at time t are assumed to experience the same level of accessibility. The generalized travel costs are computed from the zone's centroid. We observe the VKT k_i for individual i, residing in zone r at time t, and assume that this can be explained by the following specification

$$k_i^t = \alpha c_r^t + \beta o_r^t + \gamma d_r^t + \delta s_i + \phi X_i^t + \theta_t + \theta_i + \theta_i^t + \varepsilon_{it}, \quad (1)$$

where c_r^t, o_r^t, and d_r^t describe how accessibility varies across the cross-section due to differences in the road supply, the supply of other transport modes, and the spatial distribution of population density, respectively. These variables are defined by (3), (4) and (7)-(8). s_i^t denotes the distance to the centroid; X_i^t is a vector of socioeconomic characteristics; θ_i and θ_i^t represent the

unobserved time-invariant and time-varying individual-specific effects, respectively; θ_t is the time-specific effect; and ε_{it} is a normally distributed random error term.

We construct two balanced panels (1998-2005 and 2005-2017). Assuming that individual i reside in zone r at time t and in zone r^* at time $t+1$, the first-difference specification becomes

$$\Delta k_i = \alpha\Delta c_{rr^*} + \beta\Delta o_{rr^*} + \gamma\Delta d_{rr^*} + \delta\Delta s_i + \phi\Delta \mathrm{X}_i + (\theta_{t+1} - \theta_t) + (\theta_i - \theta_i) + \left(\theta_i^{t+1} - \theta_i^t\right) + (\varepsilon_{it+1} - \varepsilon_{it}), \quad (2)$$

where Δ denotes the change in a variable between time t and t+1. The explicit formulations of Δd_{rr^*}, Δc_{rr*} and Δo_{rr*} are provided in (9)–(11). The time-invariant unobserved individual-specific effect $(\theta_i - \theta_i)$ cancels out, whereas the time-varying individual-specific effect $(\theta_i^{t+1} - \theta_i^t)$ does not. The unobserved time-specific effect is given by $(\theta_{t+1} - \theta_t)$. Note that the outcome k_i captures the joint decision of car ownership and driving distance.

The accessibility measures are calculated as follows. Assume that the demand for VKT is ruled by a nested logit model, where car is in one nest and all other modes are in another nest. Assume further that the logsum parameter is λ and the number of jobs in destination zone r' at time t is $w_{r\prime}^t$. Then the logsum by car and other modes, respectively, are defined as

$$C_r^t = \ln \sum_{r\prime \in R} w_{r\prime}^t \, e^{V_{rr\prime c}^t}, \quad (3)$$

and

$$O_r^t = \frac{1}{\lambda} \ln \sum_{m \in p,w,b} e^{\lambda \, ln \sum_{r\prime \in R} w_{r\prime}^t e^{V_{rr\prime m}^t}}, \quad (4)$$

where R is the set of zones and $V_{rr\prime m}^t$ is the generalized travel cost by mode $m \in c, p, w, b$ from r to r' defined as

$$V_{rr\prime m}^t = \mu(U_{rr'm}^t + P_{rr\prime m} + \textstyle\sum_l T_{rr\prime mh}^t v_{mh}), \quad (5)$$

where $U_{rr'm}^t$ is the urban congestion charge levied on the route at time t; $P_{rr'm}$ is the pecuniary cost of a trip (fare, fuel, or depreciation); $T_{rr'mh}^t$ is the travel time; and v_{mh} is the value of time for mode m and component h (in-vehicle, transfer, waiting, and walk-access time). We assume $P_{rr'm}$ and v_{mh} are time-invariant (fixed at their 2005 values), as our interest is the effect of generalized travel times. While these terms can shift modal competitiveness and thus VKT, their effects should be similar across locations. Consequently, they should not correlate with our key explanatory variable—changes in accessibility—and are captured by the year-specific intercepts. However, the congestion charge, levied only in 2017, would vary with A and is thus time dependent.

The decay parameter μ equals -0.028 $\frac{1}{€}$ and is estimated from the travellers' observed behaviour. It reflects how sensitive travellers are to the generalized transport cost when making destination choices. A decay parameter of $-0.028\frac{1}{€}$ implies that $w_{r\prime}^t$ is multiplied with 0.25 if $V_{rr\prime m}^t$ is € 5 and by 0.004 if $V_{rr\prime m}^t$ is € 20.

The change in accessibility by car and by other modes for individual i, residing in zone r at time $t$and in zone r^*at time $t+1$, is defined as

$$\Delta C_{rr*} = C_{r*}^{t+1} - C_r^t, \quad \Delta O_{rr*} = O_{r*}^{t+1} - O_r^t \quad (6)$$

The changes in the accessibility by car and other modes in (6) depend both on the changes in the transport system and on the spatial distribution of destinations (i.e. jobs). We isolate the effect of changes in the transport system in the accessibility measures by constraining the size of the zone to unity such that

$$\begin{aligned} c_r^t &= C_r^t(w_{r'}^t = 1), \\ o_r^t &= O_r^t(w_{r'}^t = 1). \end{aligned} \tag{7}$$

We isolate the impact of the spatial distribution of destinations (jobs) on accessibility by constraining $V_{rr'c}$ to its value in $t_0 = 1998$, such that

$$d_r^t = \ln\left(\sum_{r' \in R} w_{r'}^t e^{V_{rr'c}^{t_0}}\right). \tag{8}$$

These are the accessibility measures used in (1). The change in accessibility by car and by other modes for individual i residing in zone r at time t and in zone r^*at time $t+1$ used in (2) are defined equivalently

$$\Delta c_{rr^*} = \Delta c_i = ln \sum_{r'} e^{V_{r^*r'c}^{t+1}} - ln \sum_{r'} e^{V_{rr'c}^{t}} = \ln\left(\frac{\sum_{r'} e^{V_{r^*r'c}^{t+1}}}{\sum_{r'} e^{V_{rr'c}^{t}}}\right), \tag{9}$$

$$\Delta o_{rr^*} = \Delta o_i = \frac{1}{\lambda} \ln\left(\frac{\sum_{m \in o} e^{\lambda ln \sum_{r'} e^{V_{r^*r'o}^{t+1}}}}{\sum_{m \in o} e^{\lambda ln \sum_{r'} e^{V_{rr'o}^{t}}}}\right), \tag{10}$$

and

$$\Delta d_{rr^*} = \Delta d_i = \ln\left(\frac{\sum_{r'} w_{r'}^{t+1} e^{V_{r^*r'c}^{to}}}{\sum_{r'} w_{r'}^{t} e^{V_{rr'c}^{to}}}\right)). \tag{11}$$

Total travel distance k is the product of average car trip distance l and car trip frequency f, i. e $k = l \cdot f$. If car accessibility c increases because the density of the destinations w increases in nearby zones, then l should decrease (shorter travel distances in denser areas). Moreover, parking supply—which we cannot observe directly—is likely lower in denser areas, and competing modes are more attractive there, both of which could reduce f. Hence, we expect that the parameter γ will be negative. If car accessibility increases because the generalized travel time by car decreases, then both f and l for car trips should increase. We thus expect that the parameters α is positive. Moreover, if accessibility by other modes increases, then the trip frequency by car, f, should decrease. We thus expect β to be negative.

There is rather strong correlation between Δd_{rr^*}, Δc_{rr^*} and Δo_{rr^*} in the full sample. This may impair identification, and therefore we have also estimated a specification replacing the three accessibility variables with the ratio of accessibility by other modes and accessibility by car

$$\Delta k_i = \sigma \Delta Q_{rr^*} + \delta \Delta s_i + \phi \Delta \mathrm{X}_i + (\theta_{t+1} - \theta_t) + (\theta_i - \theta_i) + \left(\theta_i^{t+1} - \theta_i^t\right) + (\varepsilon_{it+1} - \varepsilon_{it}), \text{ where} \tag{12}$$

$$\Delta Q_{rr^*} = \frac{o_{r^*}^{t+1}}{c_{r^*}^{t+1}} - \frac{o_r^t}{c_r^t}. \tag{13}$$

This ratio will depend on the density and the transport system by car and other modes.

Now, the accessibility measures (9)-(11) and (13) may change for two reasons: (i) the transport system or the spatial distribution of destinations (jobs) changes around zone r, where individual i resides at time t, and/or (ii) individual i moves to a different zone (or a combination of the two if the individual moves nearby). A change in accessibility around a given location is plausibly exogenous for individual i, since a single person can affect accessibility only marginally. By contrast, if an individual's accessibility changes because she moves, the effect may be endogenous if the unobserved individual-specific preference for driving $\left(\theta_i^t\right)$ is not constant and if changes in this preference affect whether and where to move. Because we cannot observe or explicitly account for such changes in driving preferences, they will be absorbed in the error term. In that case, ΔQ_{rr^*}, Δd_{rr^*}, Δc_{rr^*}, and Δo_{rr^*} may be endogenous.

Given the long time spans —7 or 12 years—during which some households may dissolve and new ones may form, changes in driving preferences are plausible. This is particularly likely for movers, who both decide to relocate and tend to be younger and less established in the first year of the period (e.g., forming families or starting work). To address potential endogeneity among movers, we re-estimate the models by instrumenting ΔQ_{rr^*}using the instrument

$$\Delta Q_r = \frac{O_r^{t+1}}{C_r^{t+1}} - \frac{O_r^t}{C_r^t}, \tag{14}$$

i.e., the change in accessibility in the zone of residence in period t(the first year of the period). Changes in accessibility in the zone of residence in the first year of the period should not be endogenous, since an individual cannot influence them.

3. RESULTS AND DISCUSSION

Table 1 summarizes the main estimation results. In the FD specification (2) for the full sample, the effects of density and transport supply variables are in the expected direction but smaller than in the OLS model, indicating that unobserved time-invariant individual preferences for car use correlate with the explanatory variables, for instance due to spatial sorting. The effect of accessibility by other modes Δo_{rr*} is remarkably consistent in the FD model across the two period-specific samples, whereas the impact of changes in the road transport system and in density is smaller in the later sample

Using a relative accessibility measure (other modes versus car) in (12) yields the same pattern: the pooled OLS effect is large, the first-difference effect is smaller. The third column reports results from the FD–IV estimate based on origin-zone changes is much smaller again. The coefficient retains the expected sign but is roughly 25% of the baseline FD estimate.

Improved non-car accessibility modestly reduces VKT: a one-standard-deviation increase in relative accessibility lowers car use by 1% (ATE) 3.5% (LATE). There may be other reasons why the LATE differs from the ATE in specification (12), beyond explanation (i), that accessibility changes associated with moving are endogenous because unobserved changes in preferences for driving affect both the decision to relocate and the choice of destination. The IV strategy identifies a LATE tied to variation in ΔQ_{rr^*} induced by changes around the individual's initial zone of residence r, rather than accessibility changes driven by relocation itself. This points to an alternative explanation consistent with the results, namely (ii) that the effect of accessibility changes on driving distance k is larger among individuals who move longer distances. A possible reason is that movers are, on average, younger and may be undergoing life-course transitions that make their travel behaviour more responsive to changes in accessibility.

4. CONCLUSIONS

Methodologically, the key result is that estimates based on commonly used cross-sectional variation substantially overstate behavioural responses to changes in transport supply. Using logsum-based accessibility measures and individual-level first differences reduces the estimated effects, consistent with spatial sorting bias in pooled models. An additional IV strategy based on accessibility changes around the initial residential zone yields smaller effects again, suggesting that time-varying endogeneity linked to relocation can matter over long horizons.

Substantively, the most robust finding across specifications is that improvements in non-car accessibility reduce VKT, while direct effects of road supply and destination density become limited once sorting is accounted for. These methodological insights are important for interpreting transport-demand models and for forecasting the behavioural—and by extension environmental—impacts of supply-side interventions.

ACKNOWLEDGEMENTS

We thank the Swedish research council Formas for funding, Statistics Sweden for providing the microdata, and the Swedish Transport Administration for providing historical transport system data.

REFERENCES

Adler, M. W., and van Ommeren, J. N. (2016). Does public transit reduce car travel externalities? Evidence from transit strikes. Journal of Urban Economics, 92, 106–119.
Ben-Akiva, M. E., and Lerman, S. R. (1985). Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press.
Cao, X., Mokhtarian, P. L., and Handy, S. L. (2007). Do changes in neighborhood characteristics lead to changes in travel behavior? Transportation, 34(5), 535–556.
Cervero, R., and Hansen, M. (2002). Induced travel demand and induced road investment: A simultaneous equation analysis. Journal of Transport Economics and Policy, 36(3), 469–490.
Duranton, G., and Turner, M. A. (2011). The fundamental law of road congestion: Evidence from US cities. American Economic Review, 101(6), 2616–2652.
Ewing, R., and Cervero, R. (2010). Travel and the built environment: A meta-analysis. Journal of the American Planning Association, 76(3), 265–294.
Mokhtarian, P. L., and Cao, X. (2008). Examining the impacts of residential self-selection on travel behavior: A focus on methodologies. Transportation Research Part B, 42(3), 204–228.
Ossokina, I. V., van Ommeren, J., and van Mourik, H. (2023). Do highway widenings reduce congestion? Journal of Economic Geography, 23(5), 871–900.
Wardman, M., Toner, J., Fearnley, N., Flügel, S., and Killi, M. (2018). Review and meta-analysis of inter-modal cross-elasticity evidence. Transportation Research Part A, 118, 662–681.

Table 1: Main estimates (dependent variable: annual VKT in 10 km/year)

Variable	(1) OLS Components	(2) FD Components	(3) OLS Other/Car	(4) FD Other/Car	(5) FD-IV Other/Car

Accessibility Density	-91.994*** (8.968)	-21.485*** (5.796)			
Accessibility Car	194.499*** (13.906)	48.532*** (6.967)			
Accessibility Other	-235.354*** (9.572)	-159.512*** (5.030)			
Accessibility Other/Car			-3571.998*** (120.182)	-1837.914*** (67.113)	-397.677*** (65.652)
Dist Centroid	76.418*** (2.585)	25.204*** (1.396)	108.951*** (3.781)	43.655*** (1.571)	61.676*** (1.618)
Income 1	-21.870*** (1.898)	24.615*** (3.406)	-10.482*** (1.895)	24.337*** (3.407)	24.201*** (3.409)
Income 2	550.355*** (12.621)	150.603*** (10.168)	547.816*** (12.361)	146.305*** (10.144)	146.291*** (10.143)
Income 3	1165.049*** (13.391)	501.857*** (8.452)	1104.249*** (13.687)	501.549*** (8.448)	499.589*** (8.462)
Income 4	248.952*** (4.996)	99.405*** (4.515)	219.344*** (5.324)	96.718*** (4.575)	98.470*** (4.612)
Employed	108.632*** (3.344)	77.039*** (2.858)	107.932*** (3.661)	75.130*** (2.844)	74.846*** (2.854)
Children	12.453*** (2.749)	-24.921*** (2.368)	9.431** (3.010)	-21.928*** (2.379)	-16.318*** (2.423)
Single	-88.699*** (2.920)	-32.479*** (2.279)	-95.775*** (3.212)	-34.141*** (2.301)	-39.507*** (2.308)
Company Car	-628.081*** (6.979)	-864.575*** (6.587)	-633.041*** (7.104)	-863.383*** (6.608)	-862.978*** (6.621)
Time effect early sample		40.950*** (2.000)		35.975*** (1.917)	35.542*** (1.913)
Time effect late sample		-79.334*** (2.950)		-67.944*** (2.969)	-90.340*** (2.958)
Dummy 1998	1142.032*** (64.399)		2990.416*** (127.292)		
Dummy 2005	1182.594*** (64.299)		3023.552*** (127.351)		
Dummy 2017	1105.304*** (64.509)		2962.022*** (128.662)		
Age_25_34	27.572*** (3.933)	-94.508*** (7.325)	10.917** (4.114)	-96.855*** (7.312)	-99.706*** (7.317)
Age_35_44	59.781*** (3.339)	64.008*** (5.820)	48.391*** (3.380)	62.810*** (5.802)	63.762*** (5.833)
Age_45_54	132.207*** (3.191)	163.506*** (4.382)	126.068*** (3.319)	162.024*** (4.382)	163.708*** (4.428)
Age_55_64	86.429*** (2.345)	121.423*** (2.974)	83.931*** (2.556)	120.200*** (2.979)	121.956*** (3.011)
R2	0.328	0.037	0.324	0.036	0.035
Num. Obs.	5,683,682	2,841,841	5,683,682	2,841,841	2,841,841
Weak Instruments					1480379.232
Wu-Hausman					1197.092
p-value					0.000

*+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses; clustered at centroid level.*