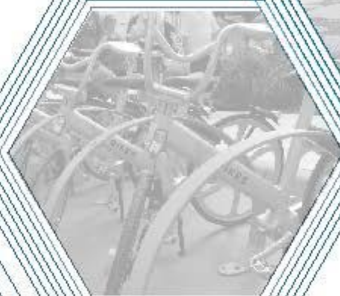

APPLICATIONS OF ACCESSIBILITY ANALYSIS FOR PREDICTING TRAVEL OUTCOMES THROUGHOUT THE U.S.

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FINAL REPORT

CENTER FOR TRANSPORTATION EQUITY, DECISIONS & DOLLARS

APPLICATIONS OF ACCESSIBILITY ANALYSIS FOR PREDICTING TRAVEL OUTCOMES THROUGHOUT THE U.S.

FINAL PROJECT REPORT

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16. Abstract

Many transportation agencies, planning organizations, and local governments are interested in predicting travel outcomes like vehicle miles traveled (VMT) and transit ridership, yet most lack formal tools for evaluating the effects of individual decisions on travel behavior. However, improved access to data and computing capabilities are enabling more agencies to develop accessibility metrics—describing access to destinations by various modes—which are useful for characterizing the built environment and its potential impacts on travel behavior. This study presents numerous models in different geographic areas that provide strong evidence for the use of accessibility metrics in predicting VMT and transit ridership. A general trend among those models is that accessibility by walking and transit, relative to driving, corresponds with lower vehicle use and higher transit use. Vehicle ownership also plays a critical role. These methods could be applied by practitioners to gauge the potential impacts of transportation investments, parking policies, and other built environment changes on travel outcomes.

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Abstract

Many transportation agencies, planning organizations, and local governments are interested in predicting travel outcomes like vehicle miles traveled (VMT) and transit ridership, yet most lack formal tools for evaluating the effects of individual decisions on travel behavior. However, improved access to data and computing capabilities are enabling more agencies to develop accessibility metrics—describing access to destinations by various modes—which are useful for characterizing the built environment and its potential impacts on travel behavior. This study presents numerous models in different geographic areas that provide strong evidence for the use of accessibility metrics in predicting VMT and transit ridership. A general trend among those models is that accessibility by walking and transit, relative to driving, corresponds with lower vehicle use and higher transit use. Vehicle ownership also plays a critical role. These methods could be applied by practitioners to gauge the potential impacts of transportation investments, parking policies, and other built environment changes on travel outcomes.

Background

Many transportation agencies, planning organizations, and local governments are interested in predicting travel outcomes like vehicle miles traveled (VMT) and transit ridership, often as part of transportation demand management (TDM) efforts, yet most lack formal tools for evaluating the effects of individual decisions on travel behavior. Many existing tools are either too resource intensive for agencies to manage or cannot properly capture the effects of smaller transportation projects and land use changes on travel behavior (e.g., four-step travel demand models). Improved access to data and computing capabilities, however, are enabling more agencies to conduct accessibility analysis—measuring access to destinations by various modes—using sketch-planning tools, standalone platforms, or open-source applications. Accessibility metrics are useful simply for describing how well transportation systems serve different populations in different locations, but they also have great potential in capturing key built environment characteristics at all scales and translating those characteristics into travel behavior outcomes like vehicle and transit use.

Measuring and managing VMT has been of growing interest among transportation agencies. Historically, VMT has been viewed generally as a positive outcome, often linked to economic growth in the U.S., although recent research refutes the direct causal nature of that relationship, particularly in the last decade (*1*–*3*). More recently, VMT has been associated with negative outcomes such as traffic congestion, emissions (*4*, *5*), and traffic deaths (*6*–*9*). For these reasons, many local governments and transportation agencies now view transportation demand management (TDM) as an effective strategy for maintaining efficient transportation systems and mitigating the negative consequences of excess vehicle travel. Perhaps most notably, California recently mandated that VMT replace highway level of service (LOS) in quantifying the negative environmental impacts from transportation projects and new developments (*10*). Other municipalities outside of California, such as Cambridge, Massachusetts, and Arlington County, Virginia, have explicit goals to reduce vehicle travel through TDM programs (*11*).

This means, of course, that local governments and transportation agencies also need tools and methods for estimating how individual decisions and projects are likely to affect VMT. While transportation and land use policies are known to influence VMT, quantifying the impacts has proven challenging (*12*–*14*). Travel demand models are a common tool for states and metropolitan regions, but they require significant resources to run and their ability to model project level changes, particularly for non-auto modes, is limited (*15*–*17*). More advanced approaches like activity-based models, dynamic traffic assignment, and integrated transportation and land use models are considerably less common and require substantial additional resources (*15*, *18*, *19*).

Similarly, agencies are often interested in estimating transit ridership, partly to justify service changes and meet customer needs, but also as a way of lowering vehicle travel demand. Transit improvements and incentives are often included in TDM programs like those described above. However, estimating ridership—especially those associated with service changes—can also be a challenging task involving complex travel demand models.

Given the need for simpler tools that are sensitive to smaller projects and changes to the built environment, a range of sketch-level scenario planning tools exist. These tools often incorporate some information about transportation provision, but are typically more useful for evaluating different land use scenarios (*20*, *21*). A common approach employed for many of these tools is using what are often characterized as the "D variables," e.g., density, diversity of land uses, design of street networks, destination accessibility, and distance to transit (*22*, *23*). A recent meta-analysis validates factors like density, street connectivity, destination accessibility, and access to transit are all associated with lower VMT (*23*). In the same special issue of the Journal of the American Planning Association, researchers point to the importance of these findings for planning practice (*24*–*26*).

While easy to implement with readily available data, however, this approach has important practical limitations, including those outlined by Handy (*25*) and Næss (*27*). As an example, we consider estimating the impacts of a new, high frequency transit line on household VMT. Based on a conventional metric like distance to the nearest transit stop, this project is likely to have a relatively small effect on some households in its vicinity. Distance from the city center, meanwhile, is much more influential (*23*). In combination, these two metrics provide some idea about how well the project might connect people to jobs, yet that specific measure—access to jobs via transit—appears to be a relatively weak predictor (*22*, *23*). Moreover, neither metric accounts for the frequency of transit service, which has significant impact on transit usage (*28*). Similar issues arise when trying to predict the impacts of street design on travel behavior. The most common design metric, intersection density, does not properly reflect the potential impacts of specific transportation projects such as a critical street connection or new bicycle and pedestrian facilities.

This study, therefore, aims to position accessibility metrics that account for multimodal access to work and non-work destinations as valuable performance measures for evaluating project impacts on VMT—particularly household VMT, which accounts for 75 to 80 percent of the U.S. total (*29*, *30*)—and other travel outcomes. The motivation and need for this work are twofold: 1) accessibility metrics have a clear potential to capture important built environment characteristics and project impacts holistically, and 2) recent advancements in data availability and computing capability enable relatively straightforward computation of advanced accessibility metrics by transportation agencies and other decision-makers. The basic concept of accessibility dates back decades (*31*, *32*) and many analytical tools exist across the globe (*33*, *34*), yet despite being widely recognized among practitioners, quantitative metrics are rarely employed (*35*–*37*). A recent study of U.S. regional transportation plans found that about half establish accessibility-related goals, but only 20 percent propose explicit accessibility metrics (*38*). Among studies linking accessibility metrics to VMT, most only consider accessibility by driving (*22*). Those that include transit accessibility measures typically derive travel times from travel demand models (*39*–*42*), while others simply measure accessibility in terms of straight-line or network distance (*43*–*47*). There are also several isolated studies indicating a relationship between accessibility metrics and transit use, typically in terms of mode share (*48*–*54*).

This study builds on those past efforts by incorporating robust travel behavior data spanning a considerable geographic scope, to test the universal application of accessibility metrics for estimating travel outcomes across the U.S. The goal is offer simple, reliable methods for linking multimodal transportation investments to outcomes like VMT and transit use.

Data and methods

Overview

This study incorporates a wide range of data sources—national and local—to explore and quantify the relationships between multimodal accessibility metrics and household travel behavior, including household VMT and transit ridership. It is divided in three parts, each different in scope and focused on different travel behavior outcomes:

1. Average household VMT in the greater Boston region (proof-of-concept),
2. Individual household VMT across the U.S. (exploratory), and
3. Transit ridership in selected regions (exploratory).

General modeling approach

In developing models to understand the relationships between accessibility metrics and travel outcomes, there are two possible approaches, each serving a different purpose. The first is to include many explanatory variables—accessibility metrics, additional built environment and transportation service metrics, and detailed demographic characters—with the goal of achieving highly accurate models with small margins of error. This approach is common in travel demand modeling and sketch planning applications. The second approach is to focus specifically on accessibility metrics and several other key control measures, with the goal of understanding potential explanatory power of different accessibility metrics and their potential use in practical decision-making applications. This study is interested in the second approach.

This approach admittedly has shortcomings. For instance, an individual's economic status, line of work, stage of life, physical ability, and political views influence their travel habits in ways that our models do not capture directly. However, those individual traits are highly dynamic compared to transportation infrastructure and other built environment provisions, which often last for decades or generations, even as populations change and relocate. In other words, transportation agencies interested in lowering vehicle use or increasing transit use may be interested in the cumulative impacts of transportation investments and built environment changes over many years, with less regard for the underlying demographic characteristics of those places.

Many studies focused on the influence of the built environment on travel behavior also take interest in the potential influence of residential self-selection. That is: can changes to the built environment cause individuals to behave differently, or do built environments attract certain populations that are predisposed to behaving a certain way? This is an important line of research, especially for understanding the potential limits of built environment changes to influence travel behavior. For transportation agencies interested in facilitating certain travel habits, however, the underlying mechanisms are less important.

Due to the nature of the available data, this study relies on several modeling approaches, including nonlinear models and simple linear regression. These models are described in the following subsections of this report, under Methods.

Data sources

State Smart Transportation Initiative (SSTI)

This study relies on a set of optimized multimodal accessibility metrics developed by our research team at the State Smart Transportation Initiative (SSTI) through past work in eight states between 2015 and 2021. The methods and data used are outlined by McCahill (*55*) and McCahill et al. (*56*). They include three metrics: the number of jobs accessible by driving during the morning period, the number of jobs accessible by transit during the morning period, and the number and diversity of non-work points of interest (POIs) accessible by walking.

Each of the metrics uses gravity-based destination weighting, which has long been regarded as more theoretically sound than cumulative opportunity metrics that use a single travel time cutoff (*57*, *58*), and is common in studies relating accessibility to travel outcomes (*39*, *49*, *53*). Destination weighting is based on mode-specific travel time decay functions derived from the 2017 National Household Travel Survey (NHTS). For instance, a job that takes 25 minutes to reach by driving counts as 0.40 jobs, because 40 percent of home-based work trips take 25 minutes or longer. Walking accessibility is measured using a pedestrian impedance concept, whereby wider roads with fast traffic and poor pedestrian facilities receive a travel time penalty (*59*).

Road and pedestrian networks are based on data from HERE Technologies, which includes average observed vehicle speeds during the morning period. Transit networks are based on publicly available data in General Transit Feed Specification (GTFS) format. Jobs data are from LEHD Origin-Destination Employment Statistics (LODES) Data, produced by the U.S. Census, and POIs are from HERE Technologies. The regions for which these data are available are described in Table 1.

Accessibility analysis was conducted using Sugar Access by Citilabs (since acquired by Bentley and rebranded as CUBE Access), which includes the most current data for each region as of the acquisition date (Table 1). Driving and transit accessibility are measured at the Census block group level and walking access is measured at the block level, then aggregated to block groups using the average value. Walking accessibility is defined in terms of the number and variety of POIs reachable by walking and reported as a score between 0 and 100. POIs are divided into nine categories—bank, education, entertainment, food and drink, grocery, health, public services, recreation, and shopping—and assigned different targets and weights defined by McCahill (*55*). Points are awarded based on the corresponding travel time decay function for home-based, non-work walking trips, derived from the 2017 NHTS. For instance, the education category is assigned a target of two schools, totaling 11.1 out of 100 total points. If the nearest school is five minutes away based on pedestrian impedance, it receives a utility of 75 percent, derived from the decay function, and earns 4.2 out of 5.6 points. A second school 12 minutes away earns 50 percent, or 2.8 points. The education category therefore earns seven points. This is repeated for each category.

Table 1. Summary of data in accessibility analysis

Region	Block groups	Acquired
Seattle, Washington	2,945	2021 (via WSDOT)
Spokane, Washington	449	2021 (via WSDOT)
Eau Claire and Lacrosse, Wisconsin	636	March 2019
Boston region, Massachusetts	6,070	May 2018
Hawaii (statewide)	855	September 2018
Michiana region, Michigan	888	June 2018
Hampton Roads, Virginia	1,208	April 2018
Lynchburg, Virginia	233	April 2018
Northern Virginia (NOVA)	3,288	April 2018
Utah County, Utah	635	January 2018
Sacramento, California	1,054	March 2016
Dane County, Wisconsin	310	June 2015

U.S. Environmental Protection Agency (EPA)

The U.S. Environmental Protection Agency provides national accessibility metrics in its Smart Location Database, in addition to its National Walkability Index (*60*). These include similar metrics to those developed by SSTI but with the following key differences:

1. Access to jobs by driving and by transit are measured using a hard 45-minute threshold, as opposed to a travel time decay function.
2. The National Walkability Index is derived by combining measures of intersection density, proximity to transit stops, employment mix, and household mix. Index values range from 1 to 20, based on block group ranking.
3. Travel times between block groups are estimated using the TravelTime API, as opposed to observed traffic speeds, transit routing information, and pedestrian impedances.

The Smart Location Database contains many additional built environment characteristics such as population and employment density measures, land use diversity measures, road and intersection density measures, and measures of transit proximity and frequency. These data were updated during this study (in mid-2021) and therefore were not considered in the initial study design. They are used as proxy measures for SSTI's optimized metrics, at the national scale.

Metropolitan Area Planning Council (MAPC)

The Metropolitan Area Planning Council (MAPC) produces the Massachusetts Vehicle Census, which includes annual mileage estimates from vehicles across the state based on data from vehicle registrations, inspection records, mileage ratings, and other sources (*61*). This study incorporates the most recent summary tables, provided at the Census block group level for the period 2009 to 2014. The average daily household VMT ("mipday_phh") are estimated by multiplying the average daily mileage per vehicle by the estimated number of vehicles per household for each block group, based on the most recent data in fourth quarter of 2014.

National Household Travel Survey (NHTS)

Estimates of household VMT from across the U.S. are derived from the National Household Travel Survey (NHTS). This study uses the best estimate of annual household VMT, as reported in the NHTS (*62*), in addition to household income, count of household vehicles, and count of household members. Restricted files were obtained from the Federal Highway Administration and Oak Ridge National Laboratory, which contained Census block group indicators for each household. This allowed us to attach accessibility metrics to each household.

Local transit ridership data

Local transit ridership data were acquired through outreach to six individual transit agencies. Each agency produced location-based boarding data—by station or by geographic coordinate—for a typical weekday before the COVID-19 pandemic. After cleaning the raw data, boardings were allocated to surrounding Census block groups in proportion to their intersection with a ¼-mile buffer around the boarding location. More details are provided in Part 3.

American Community Survey (ACS)

The American Community Survey (ACS) provides estimates of total population, total number of households, median income, and total vehicle count at the block group level. This study uses data from the 2019, five-year ACS, accessed via the National Historical Geographic Information System (*63*).

Data summary

The variables used in this study are described in Table 2.

Table 2. Variables and data sources

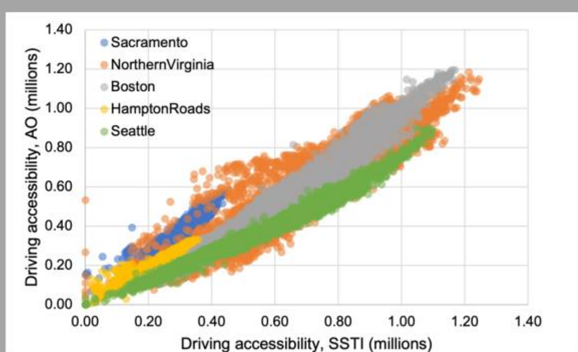
Variable	Description	Source
GEOID10	Block group ID	
Region	Region identifier	SSTI
jbDr	Access to jobs by driving	SSTI
jbTr	Access to jobs by transit	SSTI
nwWk	Access to non-work POIs by walking	SSTI
vmtMa	Average daily household VMT	MAPC
trBoard	Average weekday transit boardings	(various agencies)
pop	Population	ACS
hh	Households	ACS
hhSize	Average household size	ACS
incMed	Median income	ACS
hhVeh	Average vehicles per household	ACS
wrkDrShr	Share of workers driving	ACS
wrkTrShr	Share of workers using transit	ACS
wrkWkBkShr	Share of workers walking or biking	ACS
wrkOtShr	Share of workers using other mode	ACS
wrkTtAv	Average travel time to work	ACS
Cbsa	Metropolitan area ID	EPA
CbsaName	Metropolitan area name	EPA
CbsaPop	Metropolitan area population	EPA
CbsaEmp	Metropolitan area employees	EPA
D5ar	Jobs within 45 minutes by driving	EPA
D5br	Jobs within 45 minutes by transit*	EPA
nwi	National Walkability Index	EPA
hhIncNhts	Income for NHTS household	NHTS
hhVehNhts	Number of vehicles for NHTS household	NHTS
hhSizeNhts	Number of people for NHTS household	NHTS
hhVmtNhts	Annual VMT for NHTS household	NHTS

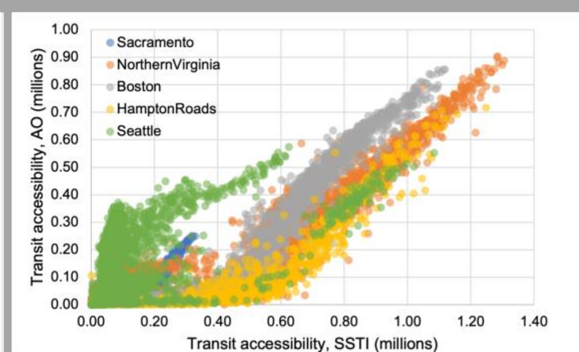
** Missing values are assigned a value of zero.*

Other available accessibility metrics

Although they were not formally used in this study, our team also assessed accessibility metrics developed by the Accessibility Observatory (AO) at the University of Minnesota for the 50 largest metropolitan areas in the U.S. in 2018.[1] These include access to jobs by driving and transit, reported for travel time thresholds between 5 and 60 minutes, at five-minute intervals. Using these data, our research team estimated the number of jobs in each five-minute band and assigned each band a weight based on the same travel time decay function used in our optimized accessibility metrics (at the midpoint of the band). These Census block-level estimates were aggregated to block groups using average values.

The figures below show how the two metrics compare for five regions with available data. While driving accessibility metrics are highly correlated, there is considerable variability in the transit accessibility metrics, especially in Seattle area, which is likely due to differences in transit route data and travel time estimates.





1. Data from the Accessibility Observatory are available at https://access.umn.edu/data/

Part 1. Average household VMT in greater Boston

The first portion of this study relies on the most robust data available: SSTI's optimized accessibility metrics and average household VMT for every Census block group in Massachusetts. As described earlier, this study is more interested in simple models to help understand the potential use of accessibility metrics in practical decision-making, as opposed to complex, predictive models. Therefore, this analysis focuses on three key accessibility measures—access to jobs by driving, access to jobs by transit, and access to non-work destinations by walking—along with several of the most influential household characteristics, according to literature: income, household size, and vehicle ownership.

Methods: Part 1

The methodology for model development consisted of sampling, exploratory data analysis, variable functional form evaluation, model coefficient estimation, model diagnostic, and validation.

Training and holdout groups were sampled for model development and validation. Through random sampling, a third of the overall data was selected in the holdout group for assessment of the reliability of the model estimates. Exploratory data analysis consisted of evaluating training data predictor variables observed distributions and correlation factors of multiple combinations. The exploratory analysis provided information to identify potential predictors and functional forms (*64*).

Model coefficients were estimated with non-linear least square approach. Linear regression fits straight lines whereas nonlinear regression generates curves as if values of the dependent variable were random. Sum of squares is a measure of the difference between the mean and each observation in the data. The objective is to make the sum of the squares as small as possible. Thus, the smaller the sum of squares the better the function fits the observed data. With nonlinear regression, several functional forms may be used for each predictor variable including trigonometric, logarithmic, and power functions. R statistical software was used to fit the models with specified functional forms. Initial values of model coefficients had to be provided for model convergence. Variables were introduced in the model incrementally, and functional forms and coefficients were monitored to identify changes due to variable interactions. Also, the order in which variables were introduced was considered, and the best combination and optimal functional for each variable was selected (*65*).

Measures of goodness of fit included model coefficients' t-tests and standard errors of residuals. In linear regression, R^2 is commonly used to explain the degree of variance in the model since the total variance is equal to the explained variance plus error variance. The arrangement produces the R^2, which is always between zero and one. However, in nonlinear regression, explained variance under linear assumptions do not apply because the explained variance and error variance do not add up to the total variance, and the R^2 is not necessarily between zero and one. As a substitute, the standard error of the results is evaluated as a measure of goodness of fit for nonlinear regression—the smaller the standard error of residuals the better the model fit.

Model validation was conducted using the holdout data. The method used for validation was cross-validation which consists of evaluating the square univariate correlation between observed and predicted response values with training and holdout data—shrinkage of cross-validation. There are not strict rules of the magnitude of shrinkage, but absolute values smaller than 0.1 indicate a reliable model (*64*).

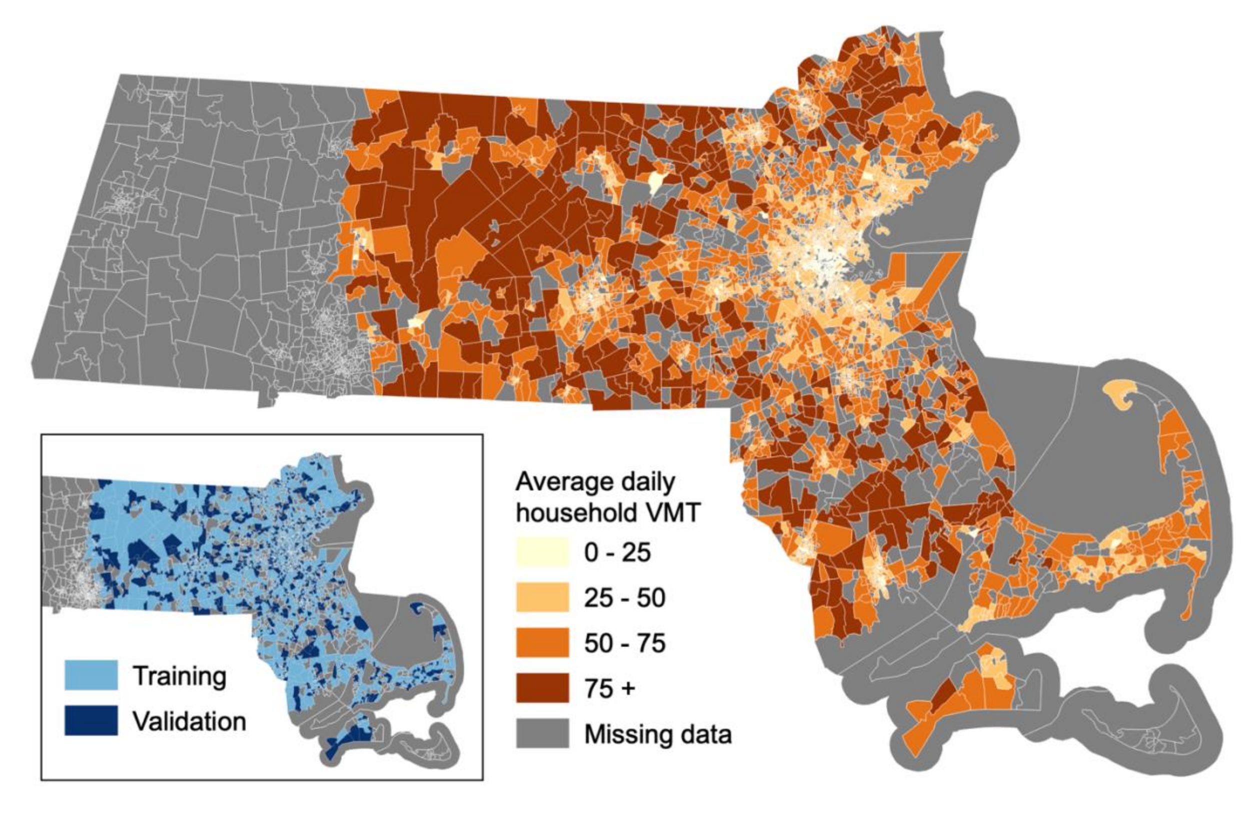


Figure 1. Average daily household VMT in Boston study area and training versus validation data

Results: Part 1

Prior to model development, we evaluated the individual relationships between household VMT and each dependent variable, several of which are depicted in Figure 3 through Figure 5. We also evaluated the functional form of each variable and the correlations among independent variables. We then developed numerous models using numerous combinations of Census data and accessibility metrics, until we arrived at several key models described below, for which the coefficients and their statistical significance, the residual standard errors (RSE), and the square univariate correlations (r^2) for validation data are shown in Table 3.

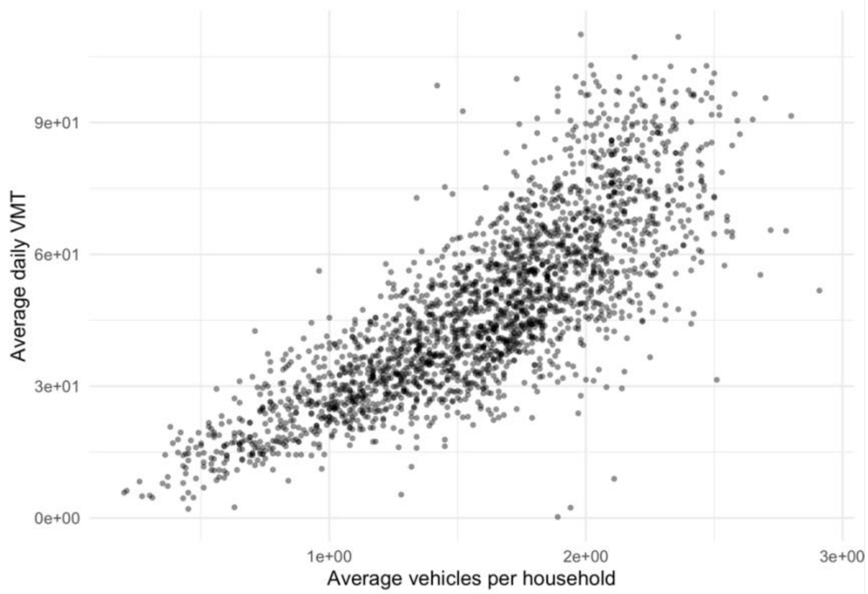


Figure 2. Average daily household VMT versus vehicle ownership (training data)

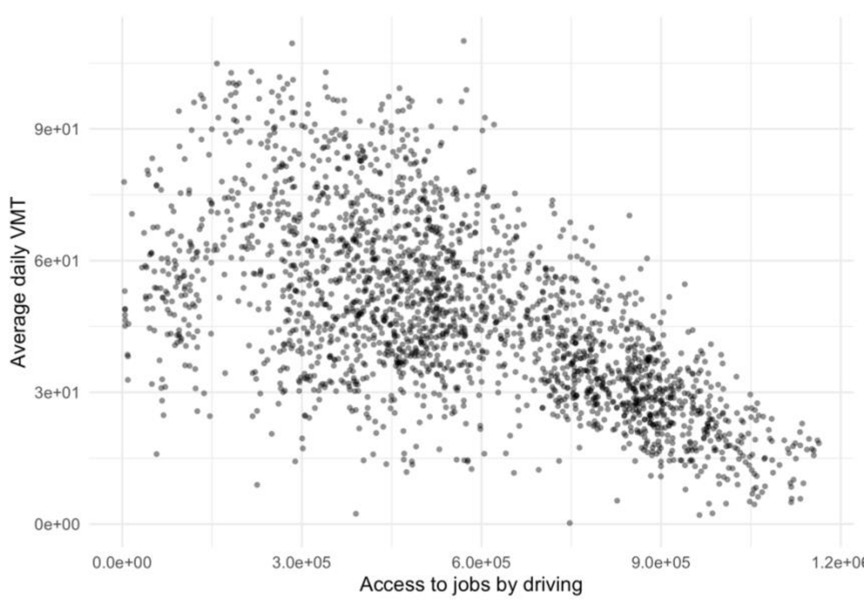


Figure 3. Average daily household VMT versus driving accessibility (training data)

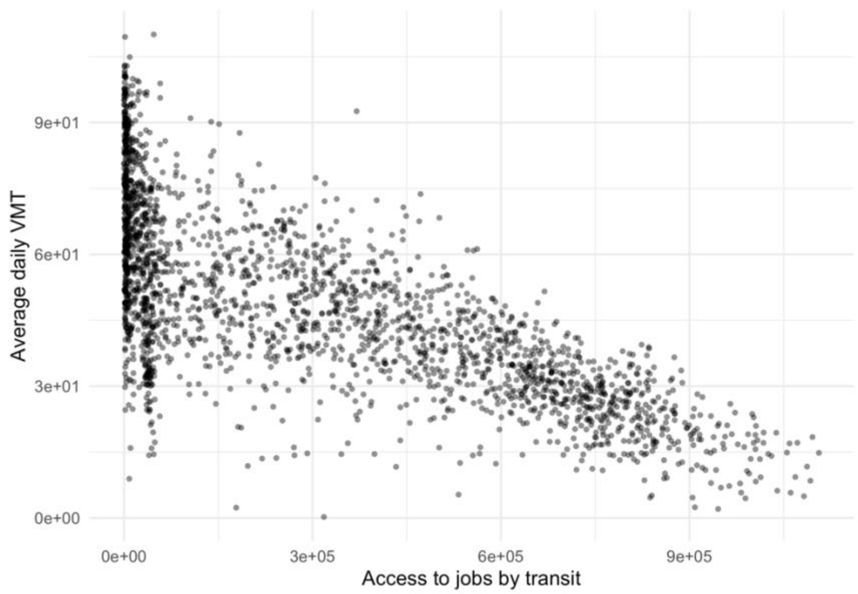


Figure 4. Average daily household VMT versus transit accessibility (training data)

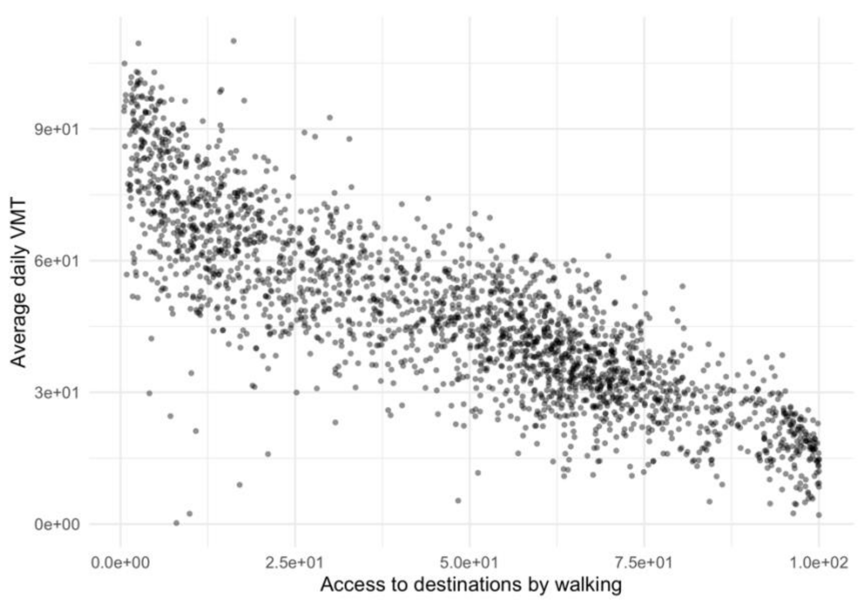


Figure 5. Average daily household VMT versus walking accessibility (training data)

Models were developed using just Census data, just accessibility metrics, and a combination of the two. As a result, we arrived at models that combine vehicle ownership data with each of the three optimized multimodal accessibility metrics. Model 1.1 incorporates just vehicles per household (omitting median income and household size), with a standard error of 11.5. Models 1.2, 1.3, and 1.4 add walking accessibility, transit accessibility, and driving accessibility in succession, for a combined standard error of 7.96. Models 1.5, 1.6, and 1.7 include just accessibility metrics, for a combined standard error of 9.74. The formulation of each is as follows:

$$\text{Model 1.1: } VmtMa = \beta_0 \times hhVeh^{\beta_1}$$

$$\text{Model 1.2: } VmtMa = \beta_0 \times hhVeh^{\beta_1} \times e^{\left(\beta_2 \times \frac{nwWk}{100}\right)}$$

$$\text{Model 1.3: } VmtMa = \beta_0 \times hhVeh^{\beta_1} \times e^{\left(\beta_2 \times \frac{nwWk}{100} + \beta_3 \times \frac{jbTr}{1E6}\right)}$$

$$\text{Model 1.4: } VmtMa = \beta_0 \times hhVeh^{\beta_1} \times e^{\left(\beta_2 \times \frac{nwWk}{100} + \beta_3 \times \frac{jbTr}{1E6} + \beta_4 \times \frac{jbDr}{1E6}\right)}$$

$$\text{Model 1.5: } VmtMa = \beta_0 \times e^{\left(\beta_1 \times \frac{nwWk}{100}\right)}$$

$$\text{Model 1.6: } VmtMa = \beta_0 \times e^{\left(\beta_1 \times \frac{nwWk}{100} + \beta_2 \times \frac{jbTr}{1E6}\right)}$$

$$\text{Model 1.7: } VmtMa = \beta_0 \times e^{\left(\beta_1 \times \frac{nwWk}{100} + \beta_2 \times \frac{jbTr}{1E6} + \beta_3 \times \frac{jbDr}{1E6}\right)}$$

The model results reveal several important trends (Table 3). In four models, vehicle ownership has a strong positive effect on VMT. While vehicle ownership alone explains a considerable amount of variation in VMT, the size of its effect drops considerably when accessibility metrics are added. In those cases, walking accessibility has the strongest negative effect on VMT, followed by transit accessibility (negative), and driving accessibility (positive). Those trends hold true even when vehicle ownership is not included.

Table 3. Model summaries: average daily VMT in Massachusetts

Coeff.	**1.1**	**1.2**	**1.3**	**1.4**	**1.5**	**1.6**	**1.7**
$ß_0$	26.93*	50.57*	49.97*	48.47*	82.62*	81.52*	74.31*
$ß_1$ (hhVeh)	1.21*	0.62*	0.62*	0.60*	—	—	—
$ß_2$ (nwWk)	—	-0.83*	-0.60*	-0.61*	-1.29*	-1.04*	-1.04*
$ß_3$ (jbTr)	—	—	-0.32*	-0.44*	—	-0.33*	-0.57*
$ß_4$ (jbDr)	—	—	—	0.15*	—	—	0.30*
RSE	11.54	8.38	8.02	7.96	10.27	9.95	9.74
$r^2_{validation}$	0.953	0.974	0.976	0.977	0.961	0.962	0.965

Significance codes: *0.001

This study points toward two of the models above for practical applications of accessibility analysis. Model 1.4 is useful for estimating VMT using accessibility metrics in combination with vehicle ownership data. In practical terms, increasing vehicle ownership or driving accessibility tends to increase VMT, while increasing transit or walking accessibility tends to lower VMT. The model has potential uses in estimating the effects of road, transit, or walking investments, land use changes, and parking policy or other factors affecting vehicle ownership. Model 1.7 is useful when no information about parking or vehicle ownership is available.

Our validation using a subset of the data confirms that the resulting models are reliable and useful for predicting household VMT throughout the Boston region. Quite notably, the square univariate correlations for the model and calibration datasets are very similar for each of the models, indicating that the models are robust and capture the variability in the data appropriately. The relationship of predicted and observed values using Model 1.4 and Model 1.7 with validation data are shown in Figure 6 and Figure 7, respectively.

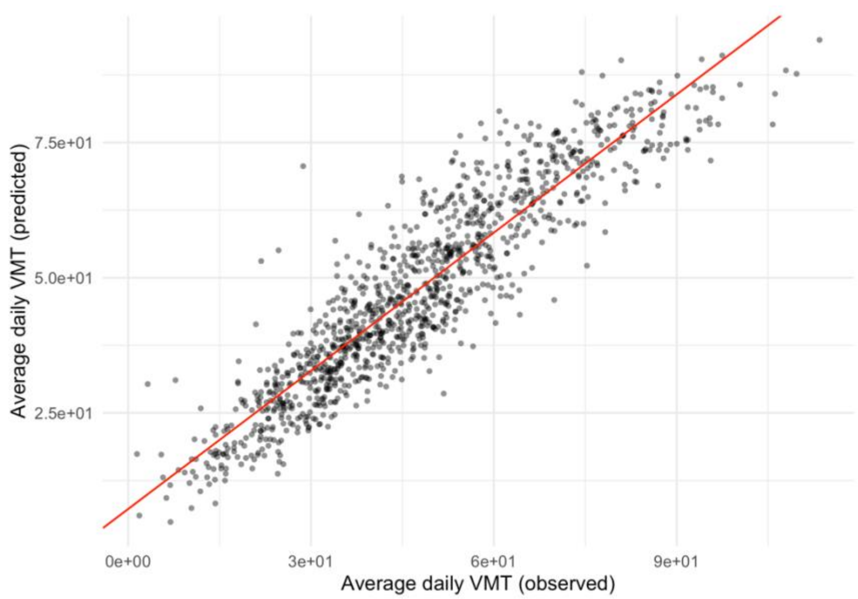


Figure 6. Observed versus predicted values based on Model 1.4: accessibility and vehicle ownership (validation data)

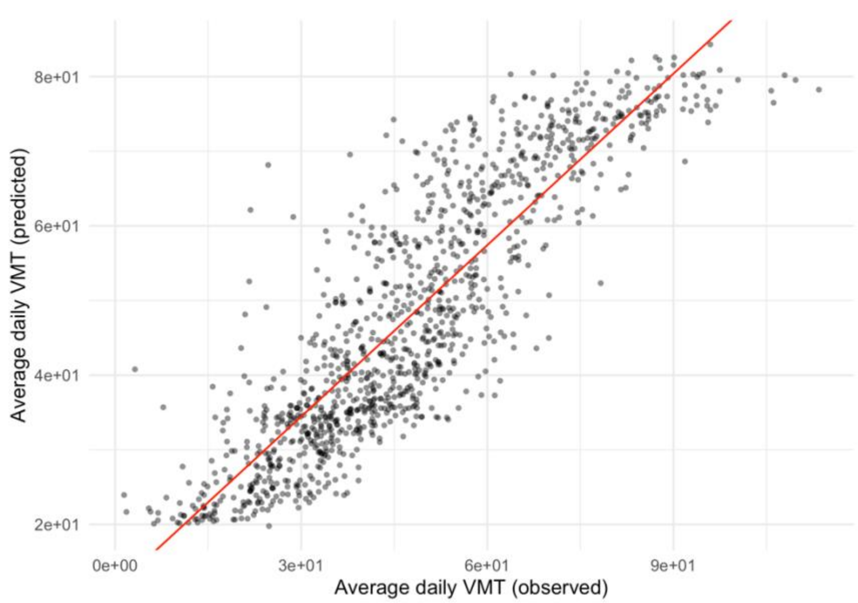


Figure 7. Observed versus predicted values based on Model 1.7: accessibility only (validation data)

Conclusions: Part 1

The results above offer important proof-of-concept for applying accessibility metrics in estimating household VMT and predicting the impacts of transportation and land use changes on VMT. Most notably, the models capture the positive effect of driving accessibility on VMT, compared to transit and walking accessibility, as opposed to the negative effect that can be observed when looking at driving accessibility alone (as in Figure 3). This points to the fact that driving accessibility is often highest in central locations where transit and walking accessibility are also high, and therefore less driving occurs. The results also point to useful non-linear model formulations for estimating household VMT, particularly when robust, aggregate VMT data are available, as in Massachusetts. The following sections of this report explore possible applications outside of Boston, including one application with sparser, more granular VMT data from throughout the U.S. and with aggregate transit ridership data for a handful of regions.

Part 2. Individual household VMT across the U.S.

This portion of the study aims to extend the concepts tested in Boston (Part 1) to a broader, national scope. The research approach evolved during this study due to: 1) limitations of the National Household Travel Survey (NHTS), from which estimates of household VMT are derived, and 2) the release of updated accessibility data from the U.S. EPA in mid-2021. The findings are currently inconclusive but point toward important future work.

Methods: Part 2

The original geographic scope of this study included the regions described in Table 1, using SSTI's optimized accessibility metrics and household-level VMT estimates from the NHTS. However, sampling limitations in the NHTS make it inadvisable to analyze just those subregions. Fortunately, the U.S. EPA's Smart Location Database was updated during this study to include three comparable accessibility measures: access to jobs within 45 minutes by driving (jbDr45), access to jobs within 45 minutes by transit (jbTr45), and a National Walkability Index (nwi).

A comparison of these metrics to SSTI's optimized accessibility metrics shows some correlation, but also important deviations (Figure 8 through Figure 10). For instance, SSTI's optimized access to jobs by driving tends to produce numbers that are around four times larger in many locations (Figure 8). These differences are likely due to differences in the underlying data (e.g., assumed travel speeds) and the fact that SSTI's metric includes jobs outside of the 45-minute threshold, weighted based on travel time.

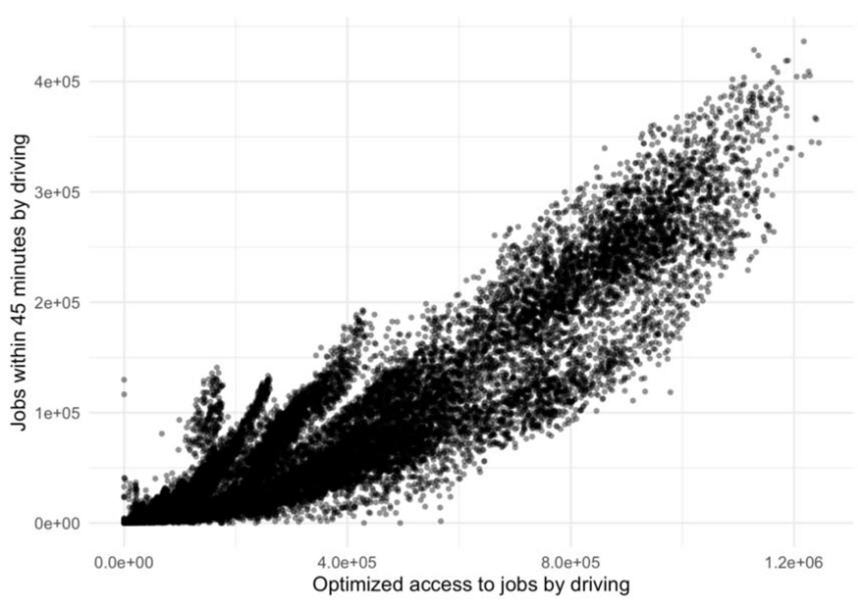


Figure 8. SSTI's optimized metrics versus U.S. EPA's metrics, for driving accessibility

The relationships between transit and walking accessibility metrics are similar, but there are areas where the EPA's metrics are considerably higher than SSTI's (Figure 9 and Figure 10). In the case of transit, these differences are likely due to differences in how travel times are estimated—i.e., using transit route information versus observed interzonal travel times. More variation is expected among the walking accessibility metrics, as shown, because EPA's metric does not incorporate POI data.

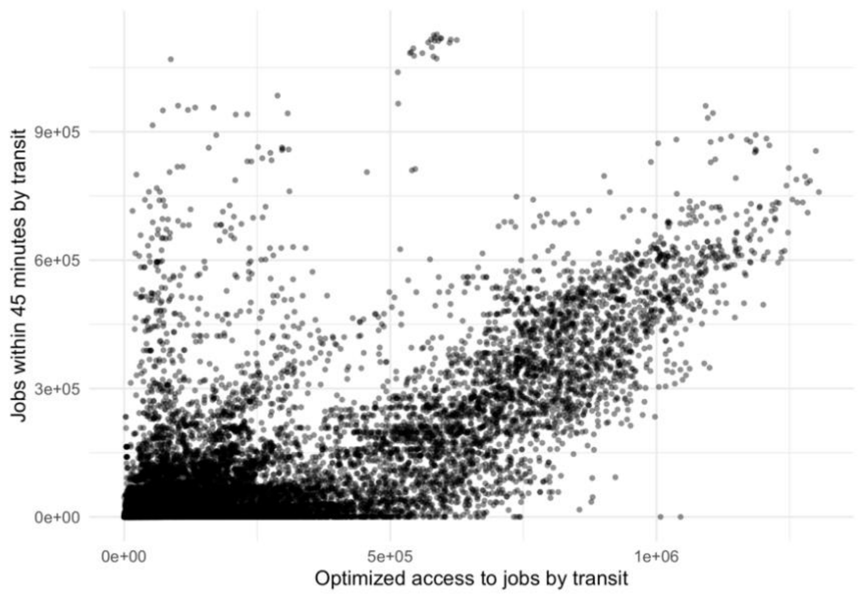


Figure 9. SSTI's optimized metrics versus U.S. EPA's metrics, for transit accessibility

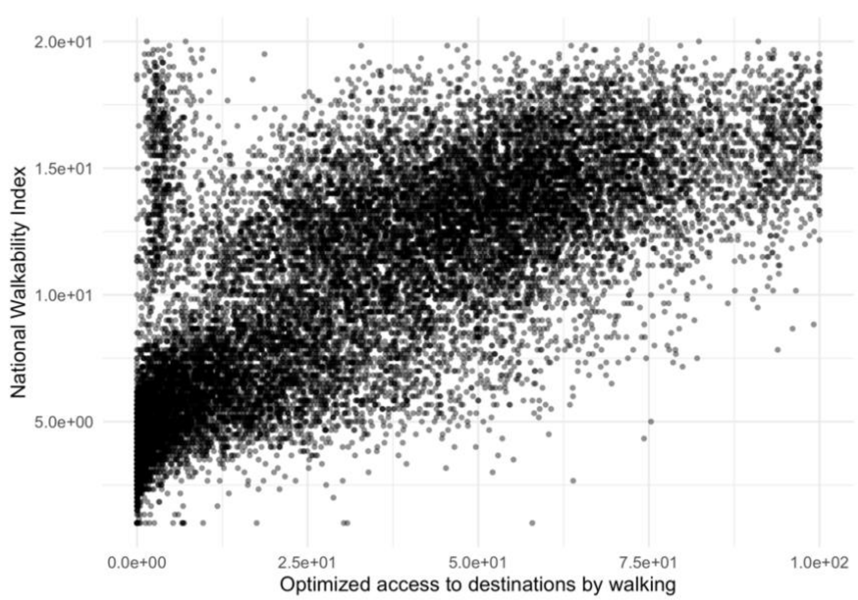


Figure 10. SSTI's optimized metrics versus U.S. EPA's metrics, for walking accessibility

Despite these differences, accessibility metrics from either source bear similar relationships to household VMT (Figure 11 through Figure 13). In this case, household VMT is transformed by taking the cube root to adjust for positive skewness.

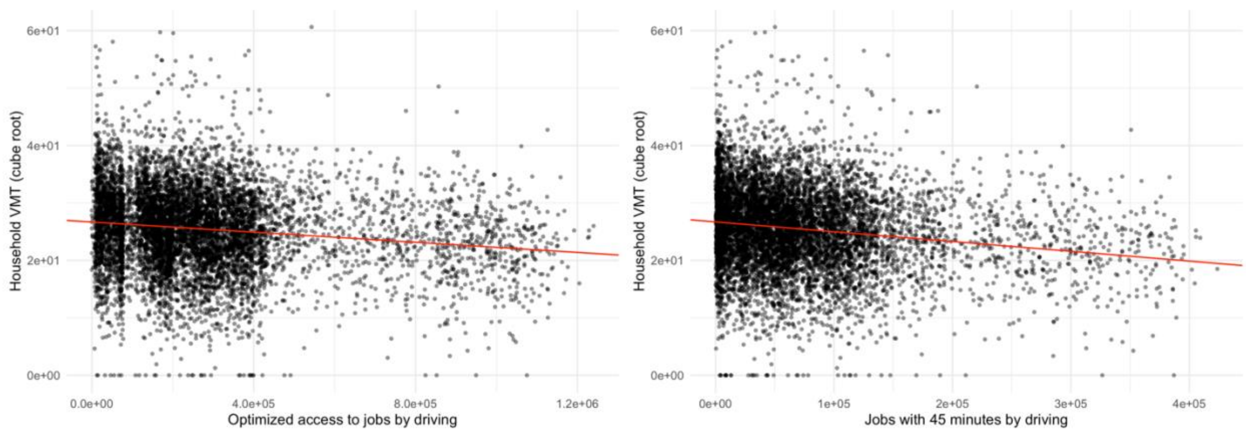


Figure 11. Annual household VMT versus driving accessibility (n = 8,066)

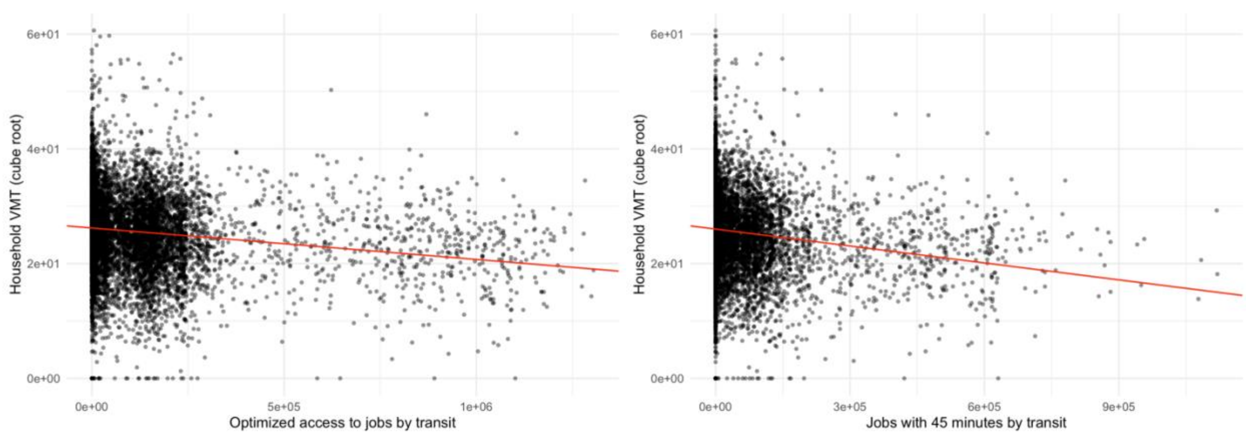


Figure 12. Annual household VMT versus transit accessibility (n = 8,066)

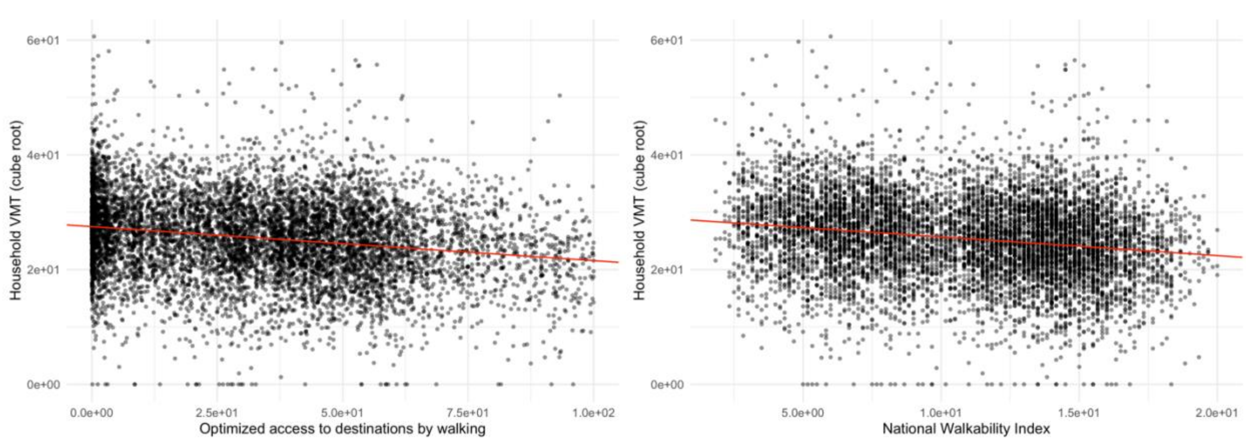


Figure 13. Annual household VMT versus walking accessibility (n = 8,066)

Results: Part 2

Based on the assessment above, national models of household VMT were evaluated using accessibility metrics from the EPA. As above, the cube root of household VMT is used to correct for positive skewness and to improve model performance. Unlike in Part 1, which incorporated non-linear modeling techniques, simple linear regression models were applied here. As the modeling results show, there are similar relationships between accessibility metrics and VMT, but the high level of variability in household VMT makes more granular modeling implausible.

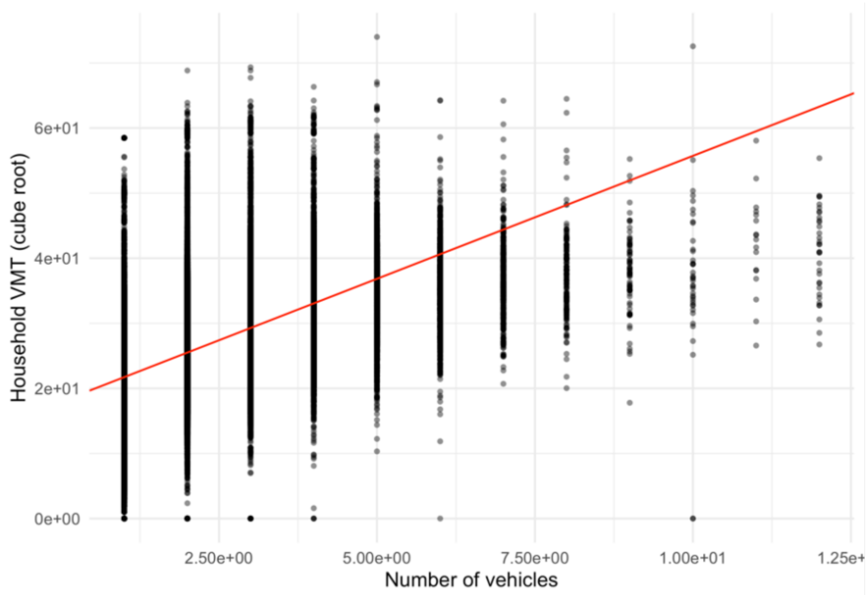


Figure 14. Annual household VMT versus number of vehicles (n = 123,447)

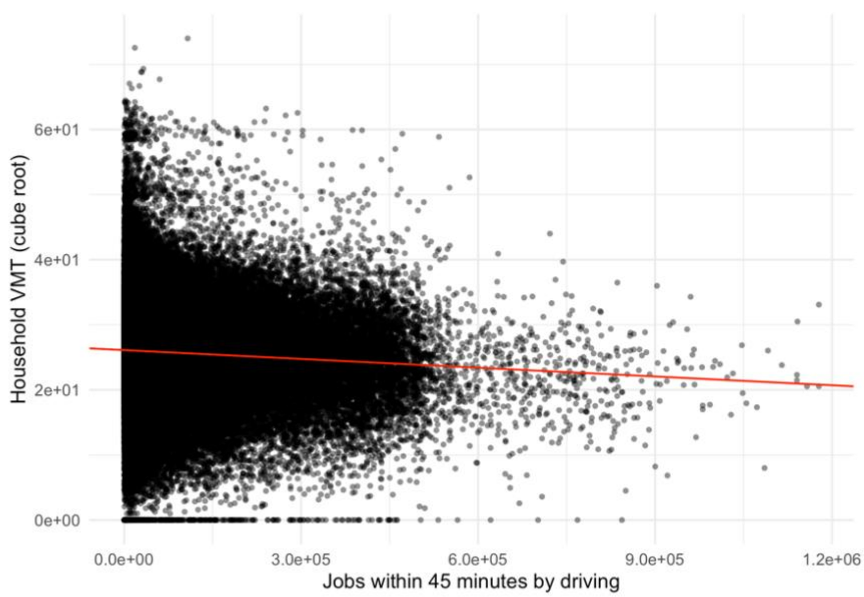


Figure 15. Annual household VMT versus driving accessibility (n = 123,447)

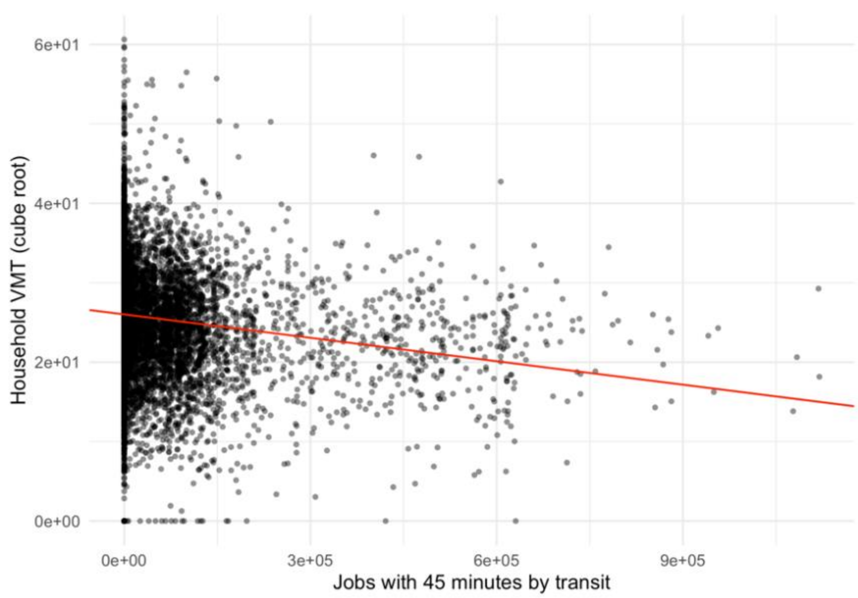


Figure 16. Annual household VMT versus transit accessibility (n = 123,447)

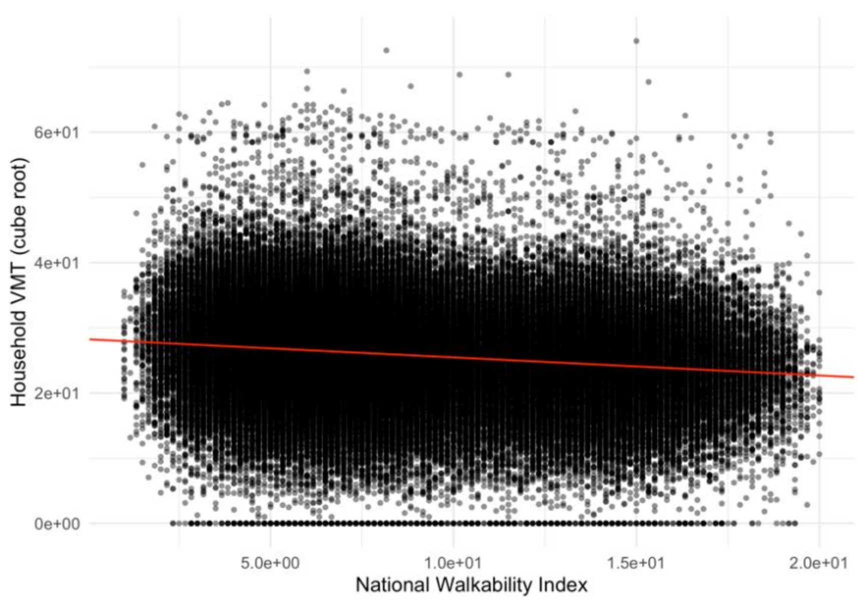


Figure 17. Annual household VMT versus walking accessibility (n = 123,447)

As shown in Table 4, the modeling results show similar trends to those observed in Part 1, but the amount of variation explained by the model is much lower ($R^2 \approx 0.3$) and vehicle ownership is the predominant factor explaining VMT in each of our models. As in Part 1, vehicle ownership has a strong positive correlation with VMT, walking and transit accessibility have negative correlations with VMT and improve the model slightly, and driving accessibility has a small positive correlation with VMT.

Table 4. Model summaries: average household VMT, nationally

Coeff.	**3.1**	**3.2**	**3.3**	**3.4**
Intercept	17.94*	18.85*	18.81*	18.84*
hhVehNhts	3.78*	3.72*	3.72*	3.72*
nwi	—	-0.088*	-.0813*	-0.106*
D5br	—	—	-5.18E-7*	-1.34E-6*
D5ar	—	—	—	2.83E-6*
R^2	0.316	0.318	0.318	0.319

Significance codes: *0.001

Conclusions: Part 2

As compared to the proof-of-concept analysis in Part 1, the national models shown here are not as conclusive, but they do offer compelling evidence that the robust model results in Massachusetts may be transferable to other parts of the U.S. Even with a simpler linear model formulation, vehicle ownership and multimodal accessibility metrics help explain VMT with the expected sign and relative magnitude.

In addition, the results of this analysis suggest that simpler cumulative accessibility metrics (i.e., the number of destinations within a predefined travel threshold) may be equally useful in predicting travel outcomes as gravity-based metrics, despite some literature suggesting the contrary (*50*).

Part 3. Transit ridership in selected regions

This portion of the study explores the relationship between transit ridership and multimodal accessibility metrics, like the VMT analysis in Part 1, but for a larger number of regions. Unlike Part 2, this analysis retains the use of optimized accessibility metrics developed by SSTI.

Methods: Part 3

For this study, our research team acquired transit boarding data by soliciting six transit agencies in selected regions. Data for bus, heavy rail (subway), and commuter rail ridership were provided. The timeframe of data we requested from all agencies followed the same language: the best location-based boarding data available that represents a typical pre-pandemic weekday, that was free of any major holidays, transit detours, or events that could impact transit ridership (e.g., college move-in days or winter holiday seasons). The resulting data are summarized in Table 5.

Boarding data were provided by transit stop or approximate boarding location, then aggregated to nearby Census block groups in GIS using methods like those described by Bree et al. (*66*). The total ridership at each location was distributed to nearby Census block groups first by creating a ¼-mile buffer around each boarding point, and then by allocating trips in proportion to the intersecting areas occupied by each block group.

Table 5. Summary of transit ridership data

Location	**Agency**	**Service type**	**Period**
Boston, MA	Massachusetts Bay Transportation Authority (MBTA)	Bus	Fall 2019
		Subway	Spring 2018
		Commuter rail	Fall 2019
Utah County, UT	Utah Transit Authority (UTA)	Bus	April & August 2019
		Rail	April & October 2019
Spokane, WA	Spokane Transit Authority	Bus	2019
Madison, WI	Madison Metro	Bus	March 3-16, 2019 (Tuesday to Thursday)
Honolulu, HI	TheBus	Bus	Spring & Fall 2019 (excluding holidays)
Seattle, WA	King County Metro	Bus	Spring & Fall 2019

These data were then combined with SSTI's multimodal accessibility data and demographic information (median income, average household size, and number of vehicles per household) from the ACS for each block group. Models were developed to estimate the total number of transit boardings associated with each block group. We evaluated a single model for all six regions and models that account for regional effects using indicator variables.

Results: Part 3

Initial data exploration suggests transit boarding data should be transformed by taking its natural logarithm, to account for positive skewness and to improve model performance. As in Part 2, simple linear regression models were applied.

Each factor has a similar but opposite relationship to transit ridership, compared to the VMT models in Part 1 and Part 2. As in other parts of this study, vehicle ownership is determined to be the most important household-level indicator. Vehicle ownership is negatively correlated with transit use (Figure 18), and accessibility metrics are positively correlated (Figure 19 through Figure 21). Those relationships are not as strong as in Part 1 (average household VMT in Boston) but they are stronger than in Part 2 (household VMT across the U.S.). Due to the complex relationship between driving and transit accessibility, we also tested a combined metric: the ratio of jobs accessible by transit to jobs accessible by driving (jbTrDr). This metric also has a notable positive relationship to transit ridership and proved useful in developing a simpler model, as described below.

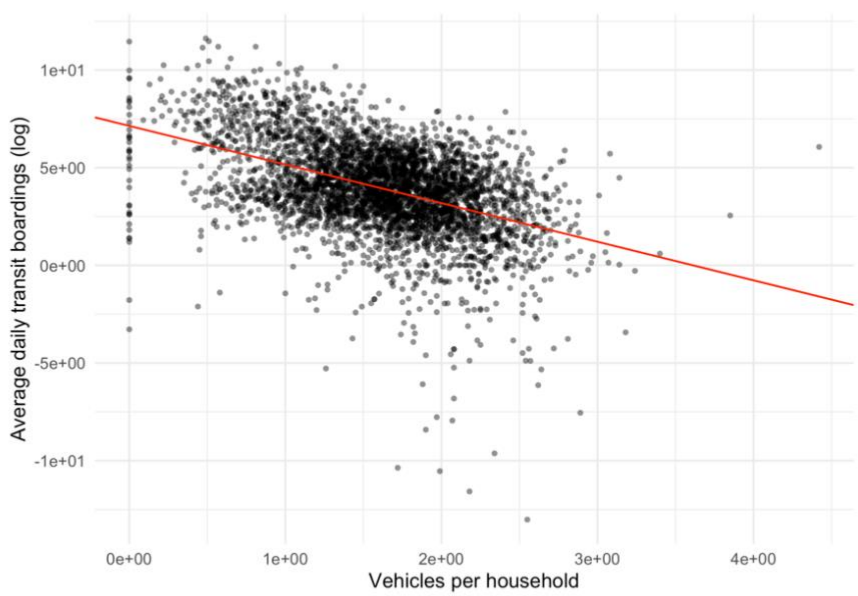


Figure 18. Transit ridership versus number of vehicles per household (n =3,858)

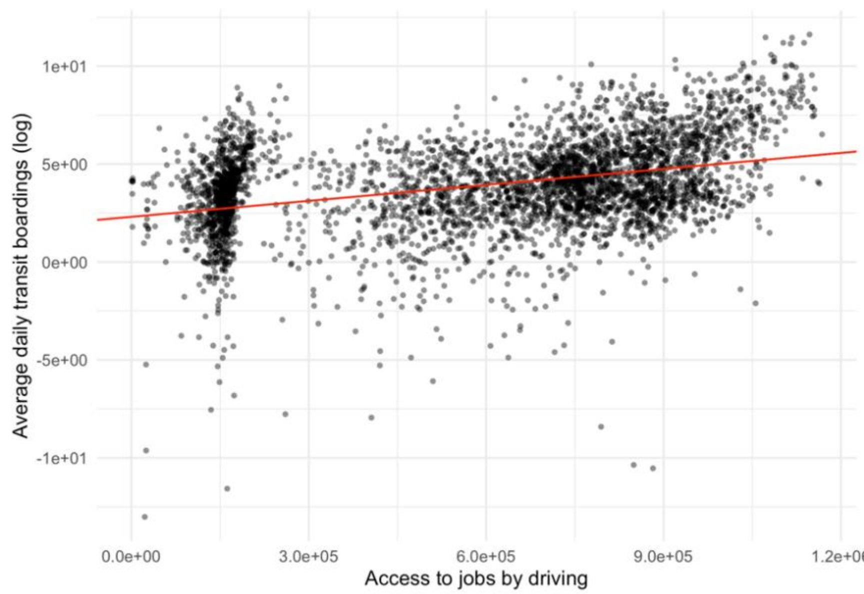


Figure 19. Transit ridership versus driving accessibility (n =3,858)

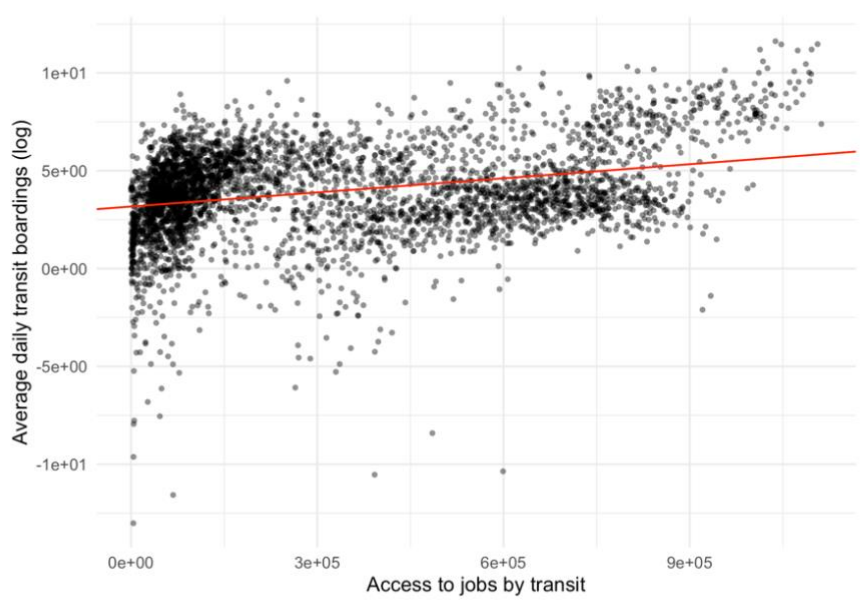


Figure 20. Transit ridership versus transit accessibility (n =3,858)

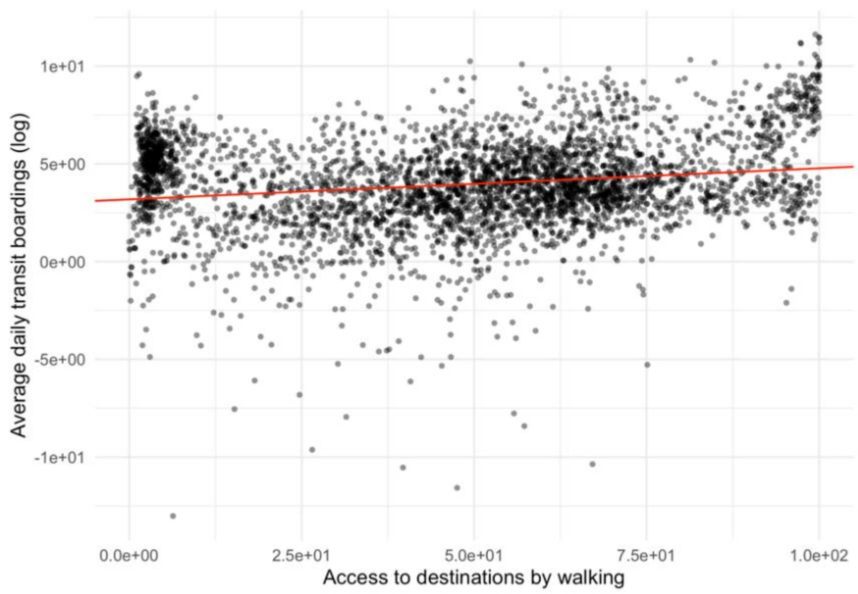


Figure 21. Transit ridership versus walking accessibility (n =3,858)

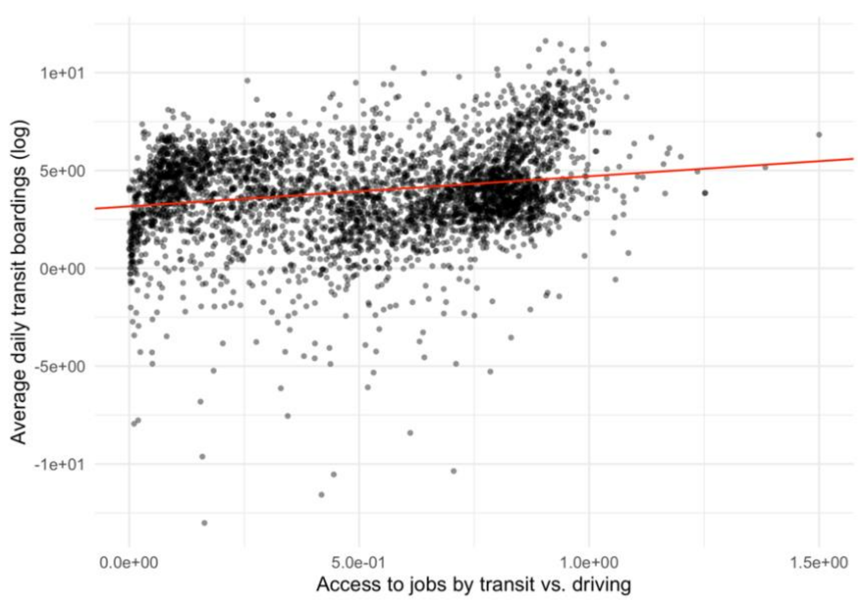


Figure 22. Transit ridership versus transit to driving accessibility ratio (n =3,858)

As shown in Table 6, the modeling results show some resemblance to those in Parts 1 and 2 of this study. For instance, vehicle ownership is a key factor and multimodal accessibility metrics considerably improve model performance. In this case, however, the relationships among accessibility metrics appear more complex. Walking accessibility appears to be considerably less influential in these models and the signs of each accessibility term are more ambiguous. In addition, Model 3.5 suggests that including regional indicators helps improve model performance considerably. In this case, transit ridership Honolulu is much higher than the model would otherwise suggest and ridership in Boston is much lower.

To account for inconsistencies among the three accessibility metrics (due largely to collinearity), we tested a combined metric (jbTrDr), as described above. This metric proved useful for simplifying the model in several ways:

1. A model with the combined metric (Model 3.5) performs just as well as a model with transit and driving accessibility as separate factors (Model 3.4).
2. In a model with the combined metric, several regional indicators are no longer necessary. Indicators for Boston, Seattle, and Spokane are significant, with Honolulu, Madison, and Utah as the reference case (Model 3.6 and 3.7).
3. Walking accessibility remains insignificant (Model 3.6 and 3.7).

The final model (Model 3.7) includes only vehicle ownership (negative), the ratio of transit to driving accessibility (positive), and indicators for three regions. The amount of variation in block group-level transit boardings explained by this model is slightly better than our national VMT models in Part 2, but still not as good as our Massachusetts-specific VMT model in Part 1.

Table 6. Model summaries: average weekday transit boardings, selected regions

Coeff.	**3.1**	**3.2**	**3.3**	**3.4**	**3.5**	**3.6**	**3.7**
Intercept	7.15*	7.42*	7.19*	5.89*	5.03*	3.71*	3.70*
hhVeh	-1.98*	-2.05*	-1.94*	-1.80*	-1.40*	-1.55*	-1.55*
nwWk	—	-3.19E-4˜	-5.85E-3*	3.69E-3˜	-1.63E-4	7.57E-4	—
jbTr	—	—	5.43E-7*	-1.31E-6*	3.62E-6*	—	—
jbDr	—	—	—	2.02E-6*	8.59E-7*	—	—
Boston	—	—	—	—	-1.86*	-0.84*	-0.78*
Honolulu	—	—	—	—	1.55*	-0.069	(*ref.*)
Madison	—	—	—	—	0.76*	-0.14	(*ref.*)
Seattle	—	—	—	—	0.79*	2.71*	2.75*
Spokane	—	—	—	—	0.53*	1.22*	1.28*
Utah	—	—	—	—	(*ref.*)	(*ref.*)	(*ref.*)
jbTrDr	—	—	—	—	—	4.31*	4.31*
R^2	0.211	0.212	0.214	0.244	0.341	0.341	0.341

Significance codes: *0.001 ˜0.05

Conclusions: Part 3

As in Part 2, the transit ridership models tested here do not provide a highly reliable approach to estimating transit ridership, but they offer compelling evidence for the use of such models and point to important considerations in calibrating those models. Like VMT models, vehicle ownership appears to be a critical factor. Unlike VMT models, however, access to non-work destinations by walking in each Census block group does not appear to be an important indicator of transit boardings in that block group. Instead, the relative access to jobs by transit compared to access by driving appears to be the key accessibility indicator of interest. There are also important regional considerations beyond the scope of this study, which may be accounted for by including additional factors or by calibrating models specifically for each region.

Discussion

Key findings and policy implications

This research promises to advance the practice of estimating VMT and other travel-related outcomes using multimodal accessibility metrics—an application of particular interest to transportation agencies and planning organizations that are already interested in accessibility analysis. While not reported here, the elasticities of VMT with respect to accessibility metrics are potentially higher than those reported in past studies (*22*, *23*), which means that these metrics could replace simpler built environment characteristics like density and land use diversity, as some have suggested (*67*). Past studies often consider accessibility in broad terms, like distance from the downtown or from the nearest transit stop. The metrics used in this study—access to destinations by different modes—are more promising from a modeling perspective and have more real-world implications for those in charge of transportation system design and land use regulations. Key findings from this study and practical policy implications are described below.

1. Vehicle ownership remains a key factor influencing travel behavior. This is useful from a modeling perspective but has mixed implications for decision-making. Vehicle ownership can be influenced by a range of factors including household income and transportation options—i.e., multimodal accessibility. In many ways, this makes it a useful proxy for those with limited data, but also less instructional for decision-makers who have limited direct influence on vehicle ownership. Nonetheless, vehicle ownership is still important to consider in combination with accessibility metrics, which could therefore influence land use and transportation decisions more directly. For instance, this work suggests that transit and walking improvements may be less effective in areas characterized by high vehicle ownership and, conversely, efforts to manage vehicle ownership—such as parking regulations and TDM policies—could have a significant effect on VMT. This view is supported by a considerable body of research suggesting the price and availability of parking is a key determinant of travel behavior (*68*).

2. Multimodal accessibility metrics can be used to predict average household VMT with a high level of reliability. This finding is confirmed by our robust models in the greater Boston area, which rely on a comprehensive VMT database and optimized accessibility metrics. Our most promising models rely only on accessibility metrics and vehicle ownership data, indicating that decision-makers can tie travel outcomes directly to those factors for which they have more direct control and omit external factors like income that, while important to consider, also have great potential to shift over time. In other words, this research suggests that policymakers can anticipate how built environment changes will likely influence travel behavior, independent of who lives in those places.

These models are not as useful for predicting individual household VMT at a national scale, according to the limited available data, but the same patterns seem to hold. This indicates that our model developed for the Boston area may be transferable, but more validation is needed. A lack of reliable household VMT data is one key obstacle to more widespread validation and adoption of the models.

3. Multimodal accessibility metrics are also useful for predicting transit ridership. As in models for predicting VMT, vehicle ownership remains a key factor in predicting transit ridership, with accessibility metrics improving model performance considerably. As with our national VMT model, a simple linear transit ridership model only explains about 30 percent of variation in transit ridership at the Census block-group level.

4. There is complicated interplay among accessibility by different modes that should be accounted for in models of travel behavior. Considered individually, driving, transit, and walking accessibility all appear to have a negative relationship to VMT and a positive relationship to transit ridership. Taken in combination, however, driving accessibility appears to have a small or positive effect on VMT, while transit and walking accessibility have increasingly negative effects. The effects of accessibility on transit ridership may be even more complex, but these complexities can be simplified by considering the ratio of transit to driving accessibility instead of each metric individually; walking accessibility does not appear to have a significant effect. The relative transit accessibility metric also seems to yield more consistent results across multiple regions.

One important implication of these findings is that driving accessibility should not be taken on its own as an indicator of travel behavior, despite its strong association with travel behavior. The highest driving accessibility is typically observed in areas where transit and walking accessibility are also highest—a function of proximity to jobs. Improving access to jobs by driving, however, such as through new highway investments or capacity improvements, will likely cause driving to increase (*12*, *69*, *70*).

Limitations and future work

Like many past studies, this research does not control for residential self-selection and, therefore, our models do not imply direct causation. For instance, while observed VMT is considerably lower in places with high walking accessibility, we cannot infer that improving walking accessibility will lower VMT among existing households. One reason is that people living in walkable neighborhoods tend to be predisposed to driving less (*70*). Nonetheless, controlling for self-selection tends to result in significant effects and higher elasticities (*23*, *70*).

Similarly, this study is based on cross-sectional snapshots of accessibility and travel behavior at a single point in time. It cannot be concluded, therefore, that incremental changes in accessibility would necessarily translate directly into changes in travel behavior. Temporal studies that measure changes in accessibility and travel behavior over time may be needed to validate assumptions about the impacts of transportation investments on travel outcomes. In the meantime, however, it is reasonably safe to assume, given our current understanding of how the built environment influences travel behavior, that cumulative changes in accessibility over time are likely to result in travel outcomes like those characterized by our models, all else being equal. In simpler terms, increasing accessibility by non-auto modes, relative to driving, is likely to lower VMT and increase the use of non-auto modes. This study provides some justification for leveraging accessibility metrics to gauge those potential impacts.

This study does not include accessibility metrics for bicycles or other emerging forms of mobility. This is due partly to unique challenges in characterizing bicycle accessibility. As with walking accessibility, there is a need for commonly accepted standards of bicycle infrastructure quality, such as level of traffic stress (*71*), along with methods for applying those standards in accessibility analysis. Our research team has experimented with different methods for applying level of traffic stress as network impedances or travel time penalties (as with our walking accessibility metrics), but there is no widely accepted approach. Moreover, any such approach requires rich, reliable data describing road characteristics and bicycle infrastructure quality for every link in the transportation network. OpenStreetMap provides high quality, crowdsourced data in some locations, but more robust data are needed. Incorporating accessibility metrics for additional modes could help improve model outcomes, but also has the potential to introduce more complex interactions among those variables.

Given the promising results in this study, researchers should continue to explore opportunities for improved modeling techniques and for leveraging more robust data sources (including local data, such as those in Massachusetts) to further calibrate and validate models linking accessibility metrics to travel outcomes. This should also involve use cases, whereby specific projects or built environment changes are evaluated using accessibility metrics and real-world outcomes are compared to model outputs.

Conclusions

This study, divided in three parts, presents important findings indicating that accessibility metrics, which describe access to destinations by various modes, can be useful in predicting travel outcomes like VMT and transit ridership.

Part 1, which leverages a unique dataset in Massachusetts, offers important proof-of-concept for applying accessibility metrics in estimating household VMT and predicting the impacts of transportation and land use changes on VMT. Models were developed by dividing Census block groups into training and validation datasets. The models explain more than 90 percent of the variation in average household VMT using just multimodal accessibility measures and information about average vehicle ownership. An important aspect of these models is that they show driving accessibility has a positive association with VMT, while transit and walking accessibility have negative associations.

Part 2 examines national models relating accessibility metrics to annual household VMT, based on observations in the National Household Travel Survey (NHTS). These models are not as conclusive as those in Part 1, but they do offer compelling evidence that the robust model results in Massachusetts may be transferable to other parts of the U.S. Even with a simpler linear model formulation, vehicle ownership and multimodal accessibility metrics help explain VMT with the expected sign and relative magnitude. This analysis also suggests that different forms of accessibility metrics, including simpler cumulative opportunity measures, can be applied.

Part 3 presents models of transit ridership in six regions across the U.S. The results, again, are not as conclusive as those in Part 1, but they offer compelling evidence for the use of such models and point to important considerations in calibrating them. Like VMT models, vehicle ownership appears to be a critical factor. Unlike VMT models, however, access to non-work destinations by walking does not appear to be an important indicator of nearby transit boardings. Instead, the relative access to jobs by transit compared to access by driving appears to be the key accessibility indicator of interest.

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