Assessing the Effect of Commute Time on Poverty in the United States

Quinn Majeski
MPA Candidate
Evans School

Introduction

Since the Great Recession there has been a growing public focus on economic inequality in the United States. Studies have shown that middle- and working-class Americans have scarcely benefitted from the economic recovery, despite notable increases in worker productivity and total personal wages (Bivens and Mishel, 2015; Saez, 2013). There are a record number of Americans living in poverty today, and a greater sustained percentage than any time since the 1980s (DeNavas-Walt and Procter, 2015).

Much of the discourse around poverty and inequality has centered on labor and wage standards, social service programs, and tax reform. Increasingly, however, transportation is being discussed as a factor in improving economic mobility. The New York Times explored the intersection in a 2015 feature, while a 2016 Washington Post story illustrated the aggregate 3.4 million years that Americans spend commuting by noting that in that time "we could have built nearly 300 Wikipedias, or built the Great Pyramid of Giza 26 times" (Bouchard, 2015; Ingraham, 2016).

In this paper I explore the statistical validity of the relationship between transportation and poverty. In doing so, I seek to answer the question: *Does the amount of time spent commuting affect the likelihood that an individual is living in poverty in the United States?*

I theorize that more time spent in transit reduces the number of hours available for other productive activities, such as networking, professional development, continuing education, and personal care. These opportunity costs limit the potential for career advancement, making it more likely that an individual will succumb to poverty. Therefore, I hypothesize that an increase in commute times is associated with an increase in individual-level poverty indicators.

Literature Review

The growing attention from press and policymakers on the role of transportation in addressing poverty is rooted in an emerging body of research that has sought to understand and characterize the link between physical mobility and economic mobility. There are several recent scholarly articles that have explored this interchange.

A 2014 study by researchers at Harvard and Berkeley examined rates of upward income mobility across different multi-county geographic regions near urban centers, which they refer to as commuting zones. They found that the prevalence of commutes lasting 15 minutes or less had a greater impact on intergenerational mobility than any other environmental factor, including neighborhood crime or single-parent status (Chetty et al, 2014).

Kaufman et al. (2015) arrived a similar conclusion in their research entitled "Mobility, Economic Opportunity and New York City Neighborhoods." Released in 2014 and updated in November 2015 to reflect new infrastructure investments, the report out of NYU's Rudin Center found that limited access to public transit in New York City neighborhoods was associated with higher levels of unemployment. The authors argue that imbalances in transit access "perpetuate issues of income equality and traffic congestion, limiting both economic and physical mobility for many in the city" (Kaufman et al, 2015, 39).

In this paper I seek to test these conclusions and build on the existing body of work by moving beyond geographically specific areas to an individual-level examination of the relationship between commute time and poverty.

Methods

The challenge of my research question is that commute time is endogenous to poverty. While I hypothesize that longer commute times are associated with greater incidences of poverty, it could also be the case that poverty causes individuals to live further away from work or to select more time consuming modes of travel transportation choices. An unemployed individual has no commute but is also more likely to be impoverished, leading to a correlation between the independent variable and the error term. Excluding unemployed individuals, however, creates a non-random sample that could produce biased results.

To address the endogeneity and potential bias inherent in my research question, I employ a quasi-experimental design using an instrumental variable for commute time. This approach simulates a natural experiment by using a two-stage regression process. First the endogenous independent variable is regressed on a separate variable known as the instrument, which is correlated with the independent variable but uncorrelated with the outcome variable. Second, the instrumental variable is used in place of the endogenous variable in a second-stage regression with the other independent variables. Although less efficient, instrumentation reduces the endogeneity and allows for an unbiased estimation of the effect of the endogenous variable.

I use the following specification for my instrumental variable (IV) model:

$$Y = \beta + \beta_1(commute) + \beta_2(age) + \beta_3(race) + \beta_4(gender) + \beta_5(education) + \beta_6(english) + \varepsilon$$

where Y is the outcome; commute is the hypothesis variable measuring minutes of commute time; age, race, gender, years of education, and English language proficiency are controls; and ε is the error term.

The control variables in the model account for variations in poverty that are common to certain socioeconomic conditions. Women, children, African Americans, Latinos, Native Americans, less educated individuals, and non-native English speakers all experience higher than average incidences of poverty in the United States (DeSilver, 2014; DeNavas-Walt and Proctor, 2015).

The outcome variable, whether or not an individual is living in poverty, is measured by whether an individual is receiving public assistance benefits. I use public assistance as my outcome variable because it offers an indicator of poverty that can be separated from whether or not an individual is employed. Although poverty has a clear connection to unemployment, many people who work low-wage jobs are nonetheless impoverished and receive public assistance.

This is in contrast to the other principal method of measuring of poverty: whether or not an individual is living below the poverty level. Because most individuals derive income from employment, and people with jobs are likely to have longer commutes than those who are unemployed, using poverty level as an outcome variable compounds endogeneity concerns.

By making the outcome variable public assistance, my specification circumvents further concerns of omitted variable bias and endogeneity. As public assistance is a categorical variable, I use an IV probit regression to estimate the effect of the hypothesis variable on the probability of receiving public assistance.

Instrumental Variable Selection

The instrumental variable I use for this specification is state road miles per capita. As an instrument, the relationship with the hypothesis variable is straightforward in theory: a more expansive network of roadways reduces congestion by providing a greater quality and quantity of route options, thereby lowering commute times.

There are two challenges to the theory supporting this relationship. First, there are modes of travel that do not make use of roadways, including fixed rail, ferries, and bicycle and pedestrian pathways. Second is the concept of induced demand, in which adding new highway capacity decreases congestion in the short term before returning to a long-term equilibrium due to overwhelming latent demand for peak-hour travel (Jaffe, 2015).

While walking, biking, and public transportation represent important transportation options, roadways remain the backbone of the United States transportation system. Eighty-six percent of Americans commuted by personal automobile in 2013, either alone or as part of a carpool. When you consider that most buses also travel on roadways, the percentage of commuters affected by road network usability rises to almost 89 percent (U.S. Census Bureau).

Induced demand is a well-documented phenomenon (Litman, 2015). I do not seek to dispute the concept in this paper, but rather to note its limitations in the context of my instrumental variable. Induced demand has only been demonstrated on highways and major urban arterials (Duranton and Turner, 2011). These roadways account for only eleven percent of total road miles in the United States, compared to nearly eighty-nine percent for collectors and local access roads (USDOT Bureau of Transportation Statistics, 2015). Furthermore, a comprehensive network of well-designed local streets support not just cars, but also bicycle, pedestrian, and transit mobility. Thus, while induced demand may somewhat weaken the relationship between road miles per capita and commute times, it is unlikely to substantially or wholly eliminate it.

It is equally important that the instrumental variable lack any relationship to the outcome variable, except through its effect on the endogenous hypothesis variable. For the purpose of this study, that means that road miles per capita should not affect whether or not an individual is living in poverty, except through its relationship to commute time. I postulate that there are two primary reasons to believe that this requirement is met by road miles per capita.

The first reason is that road construction and maintenance are funded predominantly by fuel taxes, vehicle fees, and tolls – revenue sources that are dedicated exclusively to transportation. Dedicated funding sources accounted for 86 percent of federal spending, 94 percent of state spending, and 53 percent of local spending on roadways in 2012. When each government share is weighted by its proportion of spending, the share of total roadway spending derived from dedicated revenue sources is 77.6 percent (Pew Charitable Trust, 2015).

The implication of this funding model is that transportation expenditures are largely independent of general fund spending. Because the majority of transportation funding comes from dedicated revenue sources, greater government spending on roadways has very little impact on availability of funds for social services, health care, and other programs that might have an effect on poverty.

The second reason is that our existing road system is not a reflection of current spending, but rather of historic investment of transportation dollars. The vast majority of roadways were built years or even decades ago, and the outlays for those projects began even earlier. In contrast, the benefits of expenditures on anti-poverty programs are expected to occur in the same fiscal year as the expenditure. This means that, even for transportation expenditures that originate from general funds, the status of existing roadways in the United States does not affect current spending on non-transportation government programs.

Based on these factors, I conclude that there is no relationship between road miles per capita and poverty except through its effect on commute times. Therefore, using road miles per capita as an instrumental variable should eliminate the endogeneity inherent in my hypothesis and outcome variables.

Data

The data that I use for most variables comes from the 2013 American Community Survey (ACS), administered by the United States Census Bureau. The ACS is an annual survey of the population of the United States, with approximately 3.5 million households contacted each year. Although only about two-thirds of households respond to the ACS, the presence of multiple residents in a households yielded data on more than 3.1 million individuals in 2013 ("PUMS Data").

State road miles per capita data are derived from the USDOT Bureau of Transportation Statistics and U.S. Census Bureau. The USDOT records the total miles of roadways in each state, including interstates, state highways, arterials, and local roadways. Per capita data are calculated by dividing state road miles by Census state population estimates. All data on state road miles is from 2013 (USDOT Bureau of

Transportation Statistics, 2015).

State road miles per capita is a continuous variable, which serves as the instrumental variable in my specification. The mean state road miles per capita is 0.013, indicating that the average state has about 69 feet of roadway per person. Similarly, the 0.012 standard deviation can be interpreted as a standard deviation of about 61 feet.

The ACS records age and years of education as continuous variables, and gender and race as categorical variables. English language proficiency is an ordinal variable that includes four levels of proficiency, as well as a designation for individuals who speak English and no other languages.

The ACS also surveys individuals on their commute time, which is measured as the average number of minutes they travel to get to work each day. The mean commute time in 2013 was 26.255 minutes, although a standard error of 23.550 indicates there is a good degree of variance in how long individuals spend traveling.

Respondents are also asked the total dollar value of any public assistance that they receive. The value includes Temporary Assistance for Needy Families (TANF) and other general cash assistance, but excludes non-cash assistance programs such as food stamps ("Subject Definitions"). I use this data to create a dummy variable, where each individual's public assistance observation is recoded based on whether or not they receive any public assistance dollars. This is the outcome variable that I use to measure whether or an individual is living in poverty.

Data Imputation

Several of the variables in the ACS dataset contain missing observations, including public assistance, years of education, and commute time. Table 1 shows the full extent of missing data for all variables. To address potential biases created by this missing data, I employ the multiple imputation using chained equations technique. Coefficients and standard errors are calculated based on five data sets combined using Rubin's rule for multiple imputations.

Table 1: Summary of Descriptive Statistics (Pre-Imputation)

	Observations	Mean/%	Missing
Receiving Public Assistance	2,590,923	100.00%	541,687
No	2,553,153	98.54%	
Yes	37,770	1.46%	
Roads per Capita	3,132,610	0.013 *(0.012)*	0
Commute	1,324,932	26.255 *(22.348)*	1,807,678
Age	3,132,610	40.823 *(23.550)*	0
Gender	3,132,610	100.00%	0
Male	1,529,229	48.82%	
Female	1,603,381	51.18%	
Years of Education	3,036,486	15.897 *(5.652)*	96,124
Race	3,132,610	100.00%	0
White	2,401,263	76.65%	
Black	333,070	10.63%	
Native American	32,932	1.05%	
Alaska Native	2,404	0.08%	
Asian	155,557	4.97%	
Pacific Islander	4,961	0.16%	
Other Race	113,829	3.63%	
Two or More Races	88,594	2.83%	
English Proficiency	3,132,610	100.00%	0
English Only	2,594,174	82.81%	
Very Good	323,703	10.33%	
Good	106,819	3.42%	
Poor	74,755	2.39%	
None	33,159	1.06%	

Results

Instrumentation

The first stage results of the IV probit specification indicate that the number of state road miles per capita has strong effect on commute time. An increase of one road mile per capita reduces expected commute time by approximately 70 minutes. However, given the low mean and a standard deviation for commute time, 0.013 and 0.012 respectively, a more appropriate interpretation of this effect would be that every ten feet of roadway per person reduces commute time by 7.9 seconds.

The results, detailed in Table 2 below, show that the instrument, state road miles per capita, is statistically significant and highly predictive of the endogenous hypothesis variable, commute time. The size of this effect includes any reduced effectiveness as a result of induced demand. These results support the theorized strength of using state road miles per capita as an instrumental variable for commute time.

Table 2: IV Probit Estimates of the Effect of Commute Time, First Stage Instrumentation

	$\beta_{Commute}$	Standard Error
Road Miles per Capita	-70.090***	*1.255*
Age	0.056***	*0.002*
Gender		
Male	*—base—*	
Female	-3.296***	*0.036*
Years of Education	0.292***	*0.004*
Race		
White	*—base—*	
Black	1.327***	*0.062*
Native American	1.071***	*0.193*
Alaska Native	-2.621***	*0.617*
Asian	2.036***	*0.094*
Pacific Islander	1.575***	*0.367*
Other Race	2.108***	*0.075*
Two or More Races	2.262***	*0.117*
English Proficiency		
English Only	*—base—*	
Very Good	1.280***	*0.050*
Good	1.932***	*0.093*
Poor	2.693***	*0.099*
None	3.778***	*0.167*

Significance: * α=*0.10,* ** α=0.05, *** α=*0.01*

Instrumental Variable Probit

The results of the IV probit model indicate that there is a positive relationship between the hypothesis variable, commute time, and outcome variable, use of public assistance. The mean marginal effect of a one minute increase in commute time is a one percent decrease in the likelihood that an individual is receiving public assistance. This effect is statistically significant at the 0.01 alpha level.

The coefficient on commute time is not as large as the coefficients on the demographic control variables, but is comparable to the coefficients on the continuous control variable years of education. A full summary of results is shown in Table 3.

Table 3: IV Probit Estimates of the Effect of Commute Time, Second Stage

	Public Assistance	Standard Error
Commute	0.010***	*0.003*
Age	-0.001**	*0.001*
Gender		
Male	—*base*—	
Female	0.265***	*0.010*
Years of Education	-0.020***	*0.002*
Race		
White	—*base*—	
Black	0.266***	*0.014*
Native American	0.316***	*0.018*
Alaska Native	0.575***	*0.045*
Asian	-0.068***	*0.012*
Pacific Islander	0.342***	*0.042*
Other Race	0.081***	*0.012*
Two or More Races	0.191***	*0.013*
English Proficiency		
English Only	—*base*—	
Very Good	0.014*	*0.008*
Good	0.039***	*0.012*
Poor	0.155***	*0.014*
None	0.184***	*0.018*

Significance: * α=*0.10*, ** α=0.05, *** α=*0.01*

Beyond commute time, the control variables included in the specification all produce the expected effects. Increases in age and years of education, which typically correlate with higher earning potential, are associated with a decrease in the probability that an individual receives public assistance. In contrast, demographic factors that are often associated with greater economic adversity have the opposite effect; being female or non-white both raise the expected likelihood of an individual receiving public assistance, although being of Asian descent lowers it. All of these coefficients are statistically significant at the 0.01 alpha level.

Possessing limited English language proficiency also raises the expected likelihood of an individual receiving public assistance, though not to the same extent as demographic factors. Although not directly related to the focus of this research, there appears to be a notable difference in coefficients between 'Good' or 'Very Good' English language skills and the 'Poor' or 'None' levels, suggesting a threshold proficiency for lowering the likelihood of receiving public assistance. All degrees of proficiency were statistically significant, with only 'Very good' failing to reach the 0.01 alpha level.

Discussion

These results appear to support my hypothesis that there is a positive relationship between commute time and poverty. An increase in commute time has a statistically significant effect on the likelihood that an individual is receiving public assistance benefits – the outcome variable that I use as an indicator of whether or not an individual is living in poverty.

These results cannot necessarily confirm the theory underpinning my hypothesis, however. A statistically significant relationship between commute time and likelihood of receiving public assistance does not prove that the opportunity cost of travel are hindering individuals efforts to advance professionally. There could be another explanation for the relationship between longer commutes and the likelihood an individual is in poverty.

Nonetheless, these findings have implications for elected officials and public managers to consider. Investments in transportation infrastructure and programs that reduce commute times can play a role in broader efforts to address poverty. As can efforts to encourage dense residential development near employment centers and fixed rapid transit lines. Greater coordination between transportation departments and social service programs could yield more productive programs and policy interventions.

In addressing poverty, efforts to reduce commute time may also be useful in alleviating the need for government spending in public assistance programs. The return on investment of transportation dollars may be greater than previously imagined when factoring in potential savings realized in in these other programs.

Conclusion

In this paper I have sought to test, on an individual level, whether commute time has any significant effect on whether or not an individual is living in poverty. Using an IV probit model with state road miles per capita as my instrument, I found that an increase in commute time results in a statistically significant increase in the likelihood that an individual receives public assistance benefits.

These results appear to lend credence to previous research, which has shown that neighborhood and regional transportation access affect employment, asset building, and intergenerational economic mobility. Such findings have important implications for policymakers in many fields and levels of government. While traffic reduction can be politically advantageous in its own right, policy tools that reduce commute times can also play a role in efforts to reduce poverty and potentially lower public assistance program costs.

The intersection of transportation and poverty is an area that is ripe for additional study. This paper builds on earlier work and contribute to a greater understanding of the subject, but additional experimental and quasi-experimental research is needed to fully understand and map the relationship between these two areas of public policy.

Works Cited

American Community Survey. "American Community Survey and Puerto Rico Community Survey 2013 Subject Definitions." Retrieved 3/9/16. <http://www2.census.gov/programs-surveys/acs/tech_docs/subject_definitions/2013_ACSSubjectDefinitions.pdf>

American Community Survey. "PUMS Data." U.S. Census Bureau. Retrieved 12/4/15. <https://www.census.gov/programs-surveys/acs/data/pums.html>

Bivens, Josh and Lawrence Mishel. "Understanding the Historic Divergence Between Productivity and a Typical Worker's Pay." September 2, 2015. <http://www.epi.org/publication/understanding-the-historic-divergence-between-productivity-and-a-typical-workers-pay-why-it-matters-and-why-its-real/>

Bouchard, Mikayla. "Transportation Emerges as Crucial to Escaping Poverty." The New York Times. May 7, 2015. <http://www.nytimes.com/2015/05/07/upshot/transportation-emerges-as-crucial-to-escaping-poverty.html?_r=0>

Chetty, R. et al. "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." Quarterly Journal of Economics 129(4), 2014: 1553-1623.

DeSilver, Drew. "Who's poor in America? 50 years into the 'War on Poverty,' a data portrait." Pew Research Center. January 13, 2014. < http://www.pewresearch.org/fact-tank/2014/01/13/whos-poor-in-america-50-years-into-the-war-on-poverty-a-data-portrait/>

DeNavas-Walt, Carmen and Bernadette D. Proctor. "Income and Poverty in the United States: 2014." U.S. Census Bureau. September 2015. <https://www.census.gov/content/dam/Census/library/publications/2015/demo/p60-252.pdf>

Duranton, Gilles and Matthew A. Turner. "The Fundamental Law of Road Congestion: Evidence from US Cities." American Economic Review. October 2011.

"Funding Challenges in Highway and Transit: A federal-state-local analysis." Pew Charitable

Trust. February 24, 2015. <http://www.pewtrusts.org/en/research-and-analysis/analysis/2015/02/24/funding-challenges-in-highway-and-transit-a-federal-state-local-analysis>

Ingraham, Christopher. "The astonishing human potential wasted on commutes." The Washington Post. February 25, 2016. <https://www.washingtonpost.com/news/wonk/wp/2016/02/25/how-much-of-your-life-youre-wasting-on-your-commute/>

Jaffe, Eric. "The One Chart That Explains All Your Traffic Woes." CityLab. March 2, 2015. <http://www.citylab.com/commute/2015/03/the-one-chart-that-explains-all-your-traffic-woes/386594/>

Kaufman, Sarah M. et al. "Mobility, Economic Opportunity and New York City Neighborhoods." New York University Wagner School, Rudin Center for Transportation Policy & Management. November 2015. < http://wagner.nyu.edu/rudincenter/wp-content/uploads/2015/11/JobAccessNov2015.pdf >

Litman, Todd. "Generated Traffic and Induced Travel: Implications for Transport Planning." Victoria Transport Institute. January 27, 2015. <http://www.vtpi.org/gentraf.pdf>

Saez, Emmanuel. "Striking it Richer: The Evolution of Top Incomes in the United States." University of California, Berkeley. September 3, 2013. <http://eml.berkeley.edu//~saez/saez-UStopincomes-2012.pdf>

"Table 1-1: Public Road Length, Miles by Functional System: 2013." USDOT Bureau of Transportation Statistics. June 2015. <http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/state_transportation_statistics/state_transportation_statistics_2015/chapter-1/table1_1>

U.S. Census Bureau. "American Community Survey, 1-Year Estimates, 2013." U.S. Department of Commerce. Retrieved 12/14/15. <http://www.census.gov/acs/www/data/data-tables-and-tools/subject-tables/>