



**A USDOT NATIONAL
UNIVERSITY TRANSPORTATION CENTER**

Carnegie Mellon University



THE OHIO STATE UNIVERSITY



**Driving Low-Income Mothers to Greater Success:
The Impact of Ridehailing on Income and Employment**

Contract # 69A3551747111

FINAL RESEARCH REPORT

Lee Branstetter ORCID ID 0000-0001-7835-0527

Beibei Li ORCID ID 0000-0001-5466-7925

Lowell Taylor ORCID ID 0000-0003-0188-5990

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation's University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Table of Contents

| | | |
|------------|--|--------------|
| 1. | Project Summary | p. 3 |
| 2. | Introduction | p. 4 |
| 3. | Spatial Mismatch in the U.S. Labor Market | p. 5 |
| 4. | Spatial Mismatch in Allegheny County | p. 6 |
| 5. | Field Experiment Description | p. 7 |
| | 5.1 Recruitment of Subjects | p. 8 |
| | 5.2 The Treatment Group | p. 9 |
| | 5.3 The Control Group | p. 10 |
| 6. | The Impact of Additional Mobility: Theoretical Considerations | p. 10 |
| 7. | Data Analysis | p. 11 |
| 8. | Results to Date | p. 13 |
| 9. | Scientific Contributions of the Study | p. 19 |
| 10. | Broader Impacts of the Study | p. 20 |
| 11. | References | p. 22 |

1. Project Summary

In many cities and towns throughout the United States, citizens with lower levels of education and skill confront challenges when seeking employment. The jobs best suited for their skills may be located in a different part of the metro area from their homes, and the existing public transportation system may not provide them with a practical way of interviewing for these jobs or commuting to them on a long-term basis. The rapid rise of ridehailing services, like Uber and Lyft, may provide a new opportunity to address these longstanding needs in a more cost-effective way. The public and private sectors may be able to share the costs of making the excess capacity in ridesharing systems available to disadvantaged citizens whose needs are not being served by the existing public transportation system. Such a creative partnership could connect our least advantaged citizens to new opportunities while also connecting our employers and businesses to human resources in an increasingly tight labor market. To examine the effectiveness of this resource at expanding the mobility of citizens with special transportation needs, our study seeks to combine a large-scale field experiment with sophisticated data analysis to evaluate the impact of ridesharing on individual mobility and employment outcomes.

This report describes a field experiment, still in the relatively early stages of subject recruitment, that could determine the impact of access to this technology for the geographically isolated urban poor on employment outcomes. Because many residents of these communities already possess smartphones with GPS location tracking capabilities, the impact of subsidized access to ridesharing on participants' mobility could be measured to a degree of granularity and precision that was impossible in earlier studies. We will eventually recruit into our field experiment approximately 650 mothers with children under 18 who lack reliable access to a personal vehicle and who are seeking better employment. 325 participants will be assigned to a control group. Another 325 will be assigned to a short-term treatment group and provided with significant access to free ride-sharing services over a limited period of time. Because our research is still ongoing, with the support of other research funds, we are not yet able to provide a definitive measure of the impact of additional mobility on employment outcomes. However, we include in this report preliminary evidence showing the impact of our provision of free Uber rides on the geographic mobility of our subjects; this impact appears to be substantial. We also include preliminary evidence from surveys of participants on their circumstances and on how they are using the additional geographic mobility provided by our program.

Like nearly every endeavor in the world, our study was impacted by the COVID crisis. Our initial pilot study was just concluding and plans for large-scale recruitment were about to scale up when the COVID crisis hit our region, leading to dramatic reductions in employment and even more dramatic declines in ridehailing service usage. As a research team, we responded by dramatically slowing our pace of recruitment for several months, only scaling up recruitment in the late fall. This necessarily slowed the pace of our study and necessarily postponed the point at which we will be able to report on our central hypotheses. Nevertheless, our study is going forward with sufficient funding from other sources, including the National Science Foundation and the Hillman Foundation, as well as in-kind support from Uber Technologies, Inc.. In this report, we include what early stage results we can.

2. Introduction

The labor force participation rate in the United States among the poorly educated is very low. For adults aged 25 and over, it is less than 60% among those with a high school degree, and less than 50% among those without a high school education. One contributing factor to low participation in the labor market is relatively high transportation costs. At least since the classic work of Oi (1976), economists have understood that labor force participation can be sensitive to quasi-fixed costs, such as transportation costs, and there is a small but important empirical literature reinforcing this idea. However, this is a literature with many open questions.

As we discuss in our literature review below, researchers seeking to estimate a causal impact of transportation costs on labor supply face a daunting challenge. The ideal empirical design would be a quasi-experiment in which transportation costs decline for some (treatment) individuals, while remaining fixed for other (control) individuals, *and* while holding all other factors fixed. As a counter-example, consider an investment in public transportation system. It is likely that the investment will reduce transportation costs more in some neighborhoods than in other neighborhoods, but because of *equilibrium effects*, many of which are anticipated, it is exceedingly difficult to tease out the causal impact of the change in transportation costs on labor supply. For instance, property values of homes near new convenient transportation hubs will likely increase, perhaps even before the completion of the new transportation project, as individuals with a high propensity to work relocate to those locations.

As is emphasized in the “spatial mismatch” literature, transportation costs are likely to be particularly burdensome for lower-paid poorly-educated workers, because these individuals often cannot afford housing near job opportunities. Prior research suggests this burden is likely to be especially intense for lower-income mothers with children at home, for whom the opportunity cost of time in transit may be especially high, given their parental responsibilities. For these individuals in particular, then, it seems likely that an exogenous decline in transportation costs might increase labor force participation.

Against this backdrop, we describe here an ongoing field experiment, in which participants are engaged for a moderate duration (6 months), during which we reduce the transportation cost for a treatment group, and compare labor force outcomes to a control group. In our proposed experiment, the reduction in transportation cost will be implemented via an innovative treatment that has high potential policy relevance—the provision of services from a ride-hailing service, Uber. We are excited by this particular intervention because of the possibility that future directions in public urban transportation may include technology-enabled individualized transportation services as an integral part of a broader transportation system—possibly a system that integrates smaller car-pooling cars or vans (even small self-driving vehicles) into a public transportation system that will also continue to rely on traditional rail and bus lines.

Thus, we view our experiment as accomplishing two goals:

- (1) Our research will be the first randomized controlled experiment designed to study the impact of transportation costs on the labor supply of a generally lower-paid population. As detailed below, we are focusing specifically on mothers with children at home, who do not have regular access to a car. We have reason to believe that this group may be particularly sensitive to a reduced cost of transportation.
- (2) Our experiment can also be thought of as an innovative “pilot program” designed to examine how one new technologies in transportation can be leveraged to improve the labor market outcomes in low-income families. In particular, if our work suggests that the flexibility afforded by ride-hailing

services improves labor force participation, this result could be provide an impetus for future research on the role of transportation innovation in improving labor market outcomes. More broadly we hope that the resulting research can be a valuable input for the design of public transportation systems in the decades to come.

3. Spatial Mismatch in the U.S. Labor Market

The spatial mismatch hypothesis centers on the idea that many workers may have poor labor market outcomes because they reside far from the job opportunities appropriate to their skill level, and the monetary or time cost of transporting these workers from their residences to job sites is high. Formal study of this problem began in the 1960s, and was spurred in part by the investigations surrounding the 1965 Watts riots in Los Angeles (McCone Commission, 1965). The investigating commission concluded that the low employment rates of Watts residents contributed to the riot, and these low employment rates were, in turn, driven by the geographic isolation of residents from skill-appropriate jobs elsewhere in the Los Angeles metro area. Lower rates of personal vehicle ownership among Watts residents not only cut off access to jobs but also access to many social services provided outside the neighborhood. The commission strongly recommended improvements in public transportation in order to boost employment outcomes and access to more services. However, city transportation budgets have limits, and the long-term shift of many low-skill jobs to the urban periphery, where population density is low and job sites are relatively far apart, has made it difficult to resolve this issue through traditional public transportation technologies. Decades after the release of the McCone Commission Report, researchers continue to find evidence consistent with a significant degree of spatial mismatch in American cities.

There is now little doubt that spatial mismatch is a serious social problem. One particularly persuasive study on spatial mismatch, by Andersson et al. (2018), uses employer-employee administrative data, combined with a person-specific job accessibility measure, to show that after a mass lay-off, lower-skilled workers were disproportionately likely to face long unemployment spells due to poor job accessibility. The study found that African Americans, females and older workers are more sensitive to travel time than other subpopulations.¹ This research is important because it provides solid evidence for the important role of transportation time costs as a key factor shaping labor market success, particularly among lower-skilled workers.

A modest literature focuses more directly on transportation costs/time as a factor affecting labor market outcomes. Black, Kolesnikova and Taylor (2014) found that participation in the labor force of married women is negatively correlated with the city's average commuting time, and provide some evidence of a causal link. Also, studies of local transportation systems provide useful evidence on the topic, e.g., Moeller and Zierer's (2018) evaluation of highway expansion in Germany, and Thierry and Trevien's study of the expansion of France's Regional Express Rail (RER).

¹ Andersson et al. also provide links to a large related literature on the topic, including review articles by Kain (1992, 2004), Ihlanfeldt and Sjoquist (1998), and Gobillon et al. (2007). It is well understood that racial discrimination in housing and labor markets can be an important factor in urban spatial mismatch (e.g., Gabriel and Rosenthal, 1996). Interestingly, Chetty and Hendren (2018) find that commuting time within a metro area is correlated with the odds that the next generation of residents escape poverty; the longer the average commute in a given county, the worse the chances of low-income families there moving up the ladder.

Of course, none of these studies mentioned in the previous paragraphs are a substitute for an experiment that exogenously varies transportation costs. The Black et al. (2014) paper, for example, shows a strong relationship between commuting time and labor force participation, but, as they acknowledge, part of that relationship could be driven by the sorting of households with high rates of labor force participation into cities where commuting times are shorter. Similarly, the research on the role of public transportation expansion demonstrates that reduced transportation costs shape labor markets, but as we mention in the introduction, these innovations have *equilibrium* effects—making it difficult to tease out causal effects on individual work behaviors.²

Finally, it is important to note that limited access to public transportation can hinder access to job opportunities (Lichtenwalter, Koeske, and Sales 2006) and can make job search difficult as well. Studies have shown that higher time and distance from jobs leads to lower search efforts. Not surprisingly, having access to a car makes job searching less costly and those with cars tend to have higher search intensity (Patacchini and Zenou 2005). Dependence on personal vehicles for job searching stands as a major barrier for lower income households who cannot afford to own a car.

4. Spatial Mismatch in Allegheny County, Pennsylvania

The suburbanization of poverty has also changed the dynamics of spatial mismatch in American cities. Policies seeking to connect lower income and lower skilled workers living in the urban core to jobs may no longer work as these lower income populations move to the suburbs (Frey, 2016). As the poor become more geographically dispersed along the urban periphery, the traditional hub and spoke model of most city mass transit systems becomes less useful. Disadvantaged residents need to move from one suburban area to another to pursue employment opportunities, but mass transit systems provide fewer links along the periphery. Some parts of the community are served by a single bus line that runs infrequently, making it challenging to secure employment, particularly third shift jobs or jobs in other suburban neighborhoods.

We see these trends and their consequences clearly in our own region of Southwestern Pennsylvania. The Allegheny County Department of Human Services *Suburban Poverty* report found that in many suburban census tracts, over 30 percent of residents do not own a vehicle. These residents face real transportation constraints, because 36 percent of suburban census tracts have limited access to public transportation and another 23 percent have only moderate access (Collins, Dalton, and Good, 2014). A study completed by the Shared Use Mobility Center argues that the suburbanization of poverty has led to longer commutes, poorer job access and increased reliance on personal vehicle ownership (APTA, 2016).

² For example, Thierry and Trevien (2017) note that their results “suggest that the arrival of the RER may have increased competition for land, since high-skilled households were more likely to locate in the vicinity of a RER station.”

Figure 1. Poverty and Opportunity Zones in Allegheny County

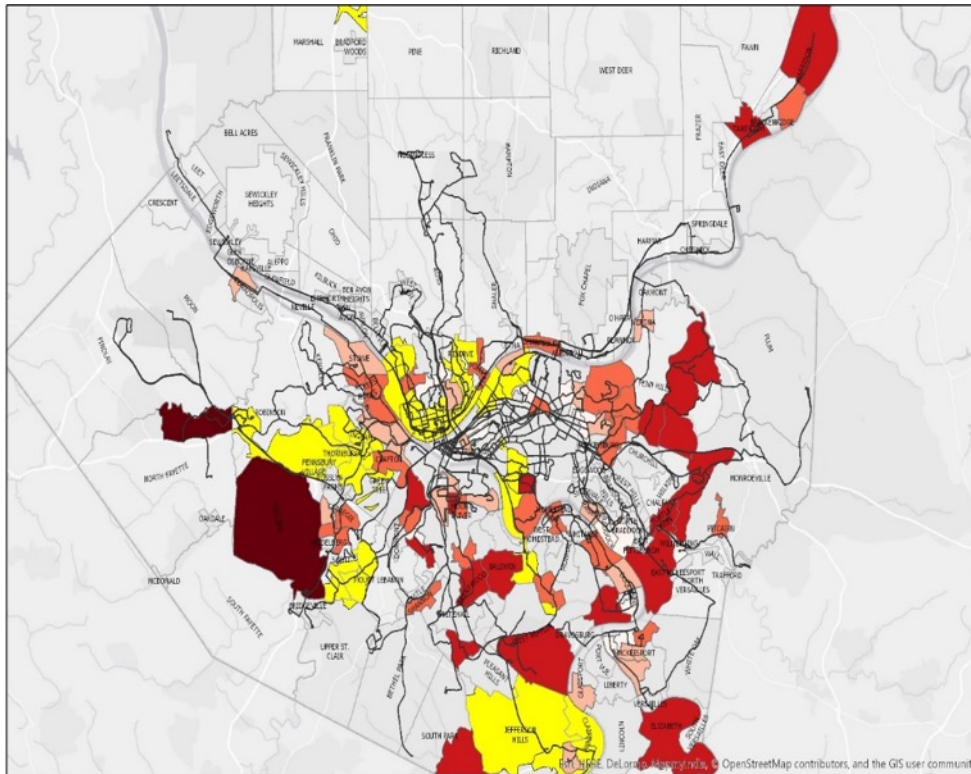


Figure 1 shows the spatial mismatch phenomenon in Allegheny County. The map uses publicly available data from the American Community Survey 5-year estimates from 2015 to create an index of neighborhood poverty based on income and education. Poorer neighborhoods are colored red, and the darker red zones indicate districts that are both poor and populous. The map also uses the Census Bureau’s Longitudinal Employment-Household Dynamics data from 2010-2014 to identify districts where low-skill jobs are being created in large numbers, which are colored yellow. It is immediately apparent that many of the poor neighborhoods are quite distant from many of the opportunity zones, and that many poor neighborhoods and opportunity zones lie well outside the urban core. When the route structure of the regional mass transit system is overlaid on top of this map, it becomes immediately apparent that the system provides limited linkages between many disadvantaged neighborhoods and the locations where residents might find appropriate jobs. In some cases the same commute that would take just minutes in a private car takes an hour or more on mass transit.

5. A Field Experiment on the Impact of Reducing Transportation Costs to Work

The goal of this project is to test the impact of reduced transportation costs on labor force participation of one group of individuals who we believe are likely to be particularly sensitive to transportation costs—women with children, who do not have regular access to a car. Black, et al. (2014) show that labor force participation decisions of women with children are highly sensitive to transportation costs. Also, the literature cited above points to the particular problems facing those who do not have regular access to a car.

With this in mind, the target group of the study is women with a child or children under age 18, who have no regular access to a car. The goal of this research is to see if labor market participation increases among women with children if they have access to convenient subsidized transportation.

5.1. Recruitment of Subjects

Recruitment of a sample of low-income mothers in the Pittsburgh region is facilitated by cooperation with Allegheny County Department of Human Services (DHS), which has built an impressive database on county residents that can help us identify eligible participants. DHS has access to Allegheny County birth records that allow us to identify mothers whose children are in the appropriate age range (under 18) at the time of our study's inception. DHS can match these data to current addresses, phone numbers, and email addresses. Thanks to a data cooperation agreement with Commonwealth of Pennsylvania's Department of Labor and Industry, DHS can also match in state administrative records on hours and wages from the unemployment insurance system, providing us with a direct measure of poverty. DHS can supplement these already-rich data with information on receipt of TANF.

DHS can use the email contact information in their data records to inform randomly selected qualifying female county residents of our study, and our partners at DHS have already invited several hundred qualifying Allegheny County residents to join the study. Because the proliferation of email and text marketing has made lower income mothers (and other U.S. residents) less likely to respond to unsolicited emails or texts of any kind, our recruitment also relies on DHS client-facing agencies and contractors, who pass along information on our project to the clients with whom they work. Potentially eligible participants are referred to a website, where they are taken through an automated screening and consent process. Prospective participants who want a phone-based screening can request this, and research assistants associated with the study will contact them in accordance with their request. This web-based screening process and the phone-based version collect enough information about our prospective participants to ensure they meet the criteria for our study. Eligible participants are randomized into the treatment or control groups and then directed to sign the appropriate consent form associated with either the treatment or control group.³

Once participants complete the consent process, they are asked to fill out an online enrollment survey that collects additional information. In return for completing this survey, they receive a \$10 gift card. Participants are invited to join the special Uber account we have set up for them, but they must accept this invitation in order to use the rides. Participants are also required to download onto their smartphones and use the "study app" described below.

One of the qualifying conditions is that participants own and regularly use a smartphone. Our experience confirms what survey research already indicates – smartphone usage has penetrated deeply into low-income urban communities, and the vast majority of women we have sought to recruit use this technology on a regular basis.

As word spreads about our study, some unqualified residents will seek to misrepresent their age, parental status, or even gender in order to qualify for the program. Fortunately, our access to DHS data records enable us to compare self-reported attributes with those in DHS records. Regular data checks of this kind enable us to recognize and disenroll unqualified individuals. To date, our experience suggests that only a very small fraction of applicants deliberately misrepresent their situations.

³ An important feature of our sampling plan is that we will be able to provide detailed characteristics of individuals in the study. This will be valuable for interpretation with respect to broader populations, i.e., will be helpful for "external validity."

Our goal is to recruit 650 women into the study—325 into the treatment group and 325 into the control group. At the time of this writing, more than 150 applicants had completed the consent process, but not all of them have completed the registration process.

5.2. The Treatment Group

“Treatment” is a roughly six-month intervention, as follows:

- *Individuals are set up with an Uber account.*⁴
 - Upon getting their Uber accounts, participants are given an initial “trial allocation” (\$30) worth of Uber rides, to make sure that they are able to use this system.
 - In the first full month of their participation in the regular study, individuals are provided with \$200 of ride-hailing credits.
 - In months 2 through 6, individuals continue to receive the \$200 credits. Obviously, \$200 per month would not be sufficient to offset the full cost of a long-distance daily commute that relied solely on Uber, but it would allow participants to supplement mass transit services with “first mile / last mile” transportation, and could also provide our participants with an alternative to mass transit or carpooling on days when time was short, the bus was running late, or typical carpooling arrangements were not feasible. In short it would provide substantial increased flexibility, which we hypothesize might be very valuable for these workers. A transit search app, described below, will facilitate the ability of our participants to combine ride-hailing and other transportation options.
- *A job-search “tool” is made available.* This tool, accessible from a smartphone or a laptop, links individuals to free services available to Pittsburgh-based job seekers through Careerlink, a state-run program designed to connect job seekers to open jobs, thereby providing modest assistance to individuals seeking to find a job or move to a new job.
- *Participants’ possession of smartphones allow us to conduct an internet-mediated short monthly survey* in which we ask about labor market activity—hours worked, wages, commute times, and job search activities. Individuals will receive \$10 per month (in the form of a pre-paid card or equivalent electronic transfer) for survey completion.
- *The same mobile app also allows us to track locations via GPS.* This is an important and innovative feature of our study. The tracker provides location data at 8-15 minute intervals, which gives us a means of verifying self-reports about employment and transportation times. For instance, if the individual reports having a job at Target on Centre Avenue in Pittsburgh, working 40 hours per week, the GPS location tracker will allow us to easily verify this. Also, we will be able to extract from the data very precise movement patterns, and it will allow us to estimate transportation times—as a supplement to self-reports on commute times.
- *The same mobile app also provides a transit-search tool that enables our participants to make the most of their access to free ridehailing by combining it with other transportation options.* This novel component of our app makes it possible for our study participants to search for all possible transit options, including mass transit (bus/subway), ride-hailing (Uber), biking, walking, or any mixed combination of these transit options, between two geographic locations. We recognize that \$200 per month will not cover our study participants’ complete transportation needs. The transit search tool makes it easier for participants venturing outside their neighborhoods to combine an Uber ride with mass transit or other options, getting much farther on their limited monthly allocation of ridehailing credits.

⁴ Our experiment will use the Uber for Business (U4B) platform, a system originally developed for businesses who wish to provide employees with subsidized transportation.

For a “treatment” individual who maintains full employment over the 6 month duration of the experiment, monetary benefit costs to the study—in the form of Uber credits and survey-response compensation—will be \$1270.

5.3 The Control Group

Individuals randomly assigned to the control group, receive similar benefits to those in the treatment group, except they will not be provided any job-contingent transportation assistance in Months 2 through 6. Thus in the control group:

- *Individuals are set up with an Uber account.*
 - Upon getting their Uber accounts, participants are given an initial “trial allocation” (\$30) worth of Uber rides, to make sure that they are able to use this system.
 - In the first full month of their participation in the regular study, individuals are provided \$170 of ride-hailing credits. But *no additional transportation assistance will be provided* after that first month. By providing individuals in the control group with this “free” \$170 in credits, plus their initial \$30 allocation, we will provide a strong incentive for members of the target population to participate, since they are assured of a valuable benefit even if they are assigned to the control group.
- *Participants are asked to download and use the app described above.*
- *We conduct a very short monthly survey* in which we ask about labor market activity—hours worked, wages, commute times, and job search activities. As with the treatment group, respondents will receive \$10 per month (in the form of an electronic transfer to a pre-paid card) for survey completion.
- *The same mobile app allows us to track locations via GPS.* Again, this is an important and innovative feature of our study, providing us with a means of verifying self-reports about employment and transportation times.
- *Finally, the same app provides transit-search capabilities to the control group, in the same way that it does for the treatment group,, enabling members of the control group to combine Uber rides with other transportation options.*

For a “control” individual, the expected cost will be approximately \$250 (assuming some non-response to surveys).

6. The Anticipated Impact of Treatment: Theoretical Considerations

The basic intuition behind our treatment is simple: an intervention that reduces commuting time is likely to have a positive impact on labor supply. We can show this idea quite simply with the following standard (static) model of labor supply. Suppose utility is a function of consumption (C) measured in dollars, and “leisure” (L), which is simply defined to be time spent *not* working or commuting to work. Now consider an individual who has L_F total hours, which she can allocate between leisure and work (plus commuting to work if she chooses to work), and has I_N dollars of non-labor income. The individual maximizes $U(C,L)$ subject to the following non-convex budget set: if she does *not* work, $C = I_N$ and $L = L_F$; if she does work, $C = w(L_F - T - L) + I_N$, where w is the hourly wage and T is time (in hours) of commuting to work. This standard model provides us with the following unambiguous prediction: A reduction in the commuting time T cannot reduce LFP for any worker, and induces positive LFP for marginal workers (who previously choose not to work).

Figure 2. The Potential Impact of Access To Ridesharing on Labor Force Participation

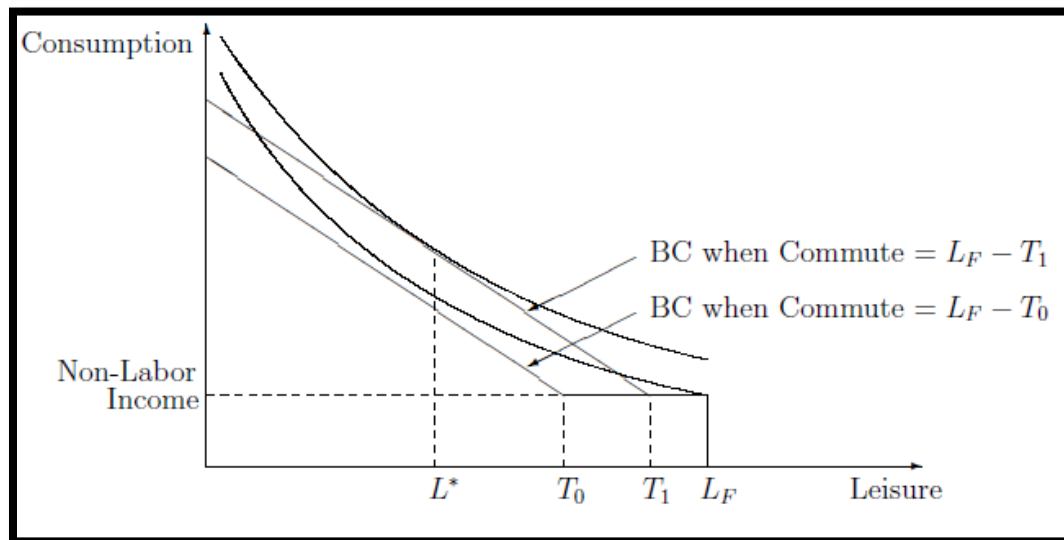


Figure 2 illustrates these ideas. If commute time is $T = L_F - T_0$ the individual will choose fulltime leisure L_F (and because she has no labor income, $C = I_N$). If commute time decreases to $T = L_F - T_1$ she chooses to work, thereby reducing her chosen leisure level to L^* (and of course has substantially higher consumption).

Black, Kolesnikova, and Taylor (2014) show that the logic of the static model extends to *dynamic* models of labor supply, and to models of *household* labor supply. In addition, they connect this logic and contemporary scholarship on these issues to the earlier literature on location and labor supply, which includes important early contributions by Oi (1976) and Cogan (1981). As we have noted, Black et al (2014) also show that as an empirical matter the LFP of married women with children is quite sensitive to commute times. They estimate that commute-time variation across cities was responsible for labor force participation differences as high as 10 percentage points for these women (from low commute-time cities to high-commute-time cities).

Our experiment thus is designed to implement a test of the basic theory of labor supply with quasi-fixed costs (commuting costs in this case) using experimental methods. To our knowledge this will be the first study of its kind, and thus will constitute a unique and potentially valuable contribution to labor economics.

In addition, as we have noted, our work can be thought of as a “program evaluation” of potential new IT-enabled modes of public transportation. In the future, new technologies might allow municipalities to include (to at least some degree) the kind of flexibility that we are providing subjects in our experiment through public support for access to ride-hailing and ride-sharing services, perhaps in the more-distant future with driverless vehicles. Our study is a first step in what we hope will be an active literature on the public policy benefits of such transportation innovations. In particular, our work will constitute a potentially important assessment of the value of such transportation for increasing the labor force participation in a particularly vulnerable population.

7. Data Analysis

The major focus of this study is to examine the impact of our intervention on labor market outcomes, including:

- effort seeking a new job (among those who don't currently have a job)
- labor force participation (LFP)
- time spent traveling to and from work (for those who work)
- hours worked per month
- wages and earnings

Because we have a randomized control trial, basic analysis will be quite simple; we can use t-tests to compare mean differences. With our intended sample sizes, 325 in each experimental condition, we anticipate having power to detect reasonable-sized treatment effects. For example, suppose that we end up with 300 usable cases in each condition (after attrition or other issues with data collection). Then suppose the overall estimated LFP in our combined sample is 0.60, with an estimated mean of 0.66 in the treatment group and 0.54 in the control group. Then the estimated standard error of the mean difference is

$$\widehat{SE} = \sqrt{0.60 \times (1 - 0.60)} \sqrt{\frac{1}{300} + \frac{1}{300}} = 0.04,$$

and the t-statistic is

$$t = \frac{0.12}{0.04} = 3,$$

which obviously is statistically significant. Even with somewhat smaller hypothesized treatment sizes, we will retain reasonable statistical power.⁵

In addition to our tests of mean differences in outcomes, we anticipate using regression-based methods, which can reduce the standard error of the estimated treatment effects, and potentially give additional insights. The most basic such regression would be

$$y_i = \beta_0 + T_i\beta_1 + X_i\beta_2 + \varepsilon_i,$$

Where y_i is the outcome of interest (earnings, LFP, average time spent commuting to work, etc.), T_i is a dummy variable indicating treatment status (so β_1 estimates the treatment effect) and X_i is a vector of individual-level characteristics (such as location, race, age, etc.). These characteristics would be drawn from the intake survey and from data collected and maintained by DHS. Given randomization, we do not need control variables to form an unbiased estimate of the treatment effect, but inclusion of the variables can help with the precision of the estimate would also be a useful check for randomization fidelity.

Importantly, our outcomes can include not only self-reports, but also outcomes determined from the GPS tracking data, *and* outcomes constructed from data provided by the DHS, which includes data on hours and wages taken from official records of the state Department of Labor and Industry. This last feature of our research design is useful for two reasons. First, having administrative data will add to the credibility of our results (and will also allow for some methodologically interesting analysis of measurement error). Second, it will allow us to do a follow-up analysis in which we can examine longer-run impacts. For instance, we may find that our transportation treatment not only increases labor force participation during the 6 months

⁵ For example, even with a treatment effect size of 0.08, our t statistic is 2, which means we have power of approximately 0.975 (based on a one-sided test).

of the study but also has a longer-term impact. In addition, we may find that at least some individuals in our treatment group continue to earn higher incomes – and therefore have less demand for social services - years after the cessation of the treatment.

We anticipate that we may have enough power with our experiment to even include simple interaction terms of the treatment variable and one of our “control variables,” thereby investigating heterogeneity in treatment. For instance, we could form a dummy variable equal to 1 for individuals who live in “transportation deserts,” to determine if our intervention is larger for these individuals. Alternatively, we could see if treatment effects are larger for mother with young children.

Finally, for some outcomes—such as employment—we may find it useful to use specifications that allow for time-varying dimensions (i.e., have a time subscript in the basic regression). For many of our analyses OLS will do, but for some outcomes (e.g., number of weeks employed over the 6 month period) other models will be employed (negative binomial regression methods, etc.)

Exploratory Analyses of Treatment on Other Outcomes. While the primary focus of our study is on the impact of the transportation experiment on employment, our design will allow us to do some “exploratory” analysis of the impact on other outcomes from the self-reported data, the GPS location tracking data, and more importantly from the DHS data.

For example, DHS records individual-level use of training programs and other social services. Also, the data include child-level outcomes, such as school truancy and disciplinary actions. It seems possible that improved access to transportation flexibility may improve family lives in ways that extend beyond employment.

Also, recall that all participants will have an app on their smartphones that regularly notes their GPS coordinates. These data will be recorded using an algorithm that assigns a unique identifier to every participant but protects his or her identity. In addition, for participants with access to ridesharing data, the data generated by our cell phone “location tracker” app will be supplemented by the pickup and drop-off data collected by the ridesharing company. It is quite possible that access to ridesharing services may enhance the mobility of participants in ways that are not always directly connected to job search or efforts to access social services. For instance, ridesharing services might enhance the ability of lower-income participants in poor, geographically isolated communities to access community amenities (parks, libraries, etc.). It could also expand their ability to consume a wider range (and higher quality) of commercial goods and services, and engage in more frequent social interaction through community events, religious services, musical performances, etc. The granularity of our user mobility data may allow us to detect or infer some of these changes in consumption and social interaction. As part of our initial efforts to explore these data, we will quantify differences in mobility between the control group and the treated groups along a number of dimensions. We plan to measure the number of unique neighborhoods (or zip codes) an individual visits per day/week. We can build upon prior analyses of individual mobility by measuring the spatial entropy of an individual’s movements over a period of time (e.g., a measure of the distribution of an individual’s movement through geographic space across distinct neighborhoods and locations). Finally, we can, in principle, compare the patterns of movement of participants with ridesharing services who reside in certain neighborhoods to members of the control group who live in the same neighborhoods, but lack access ridesharing services.

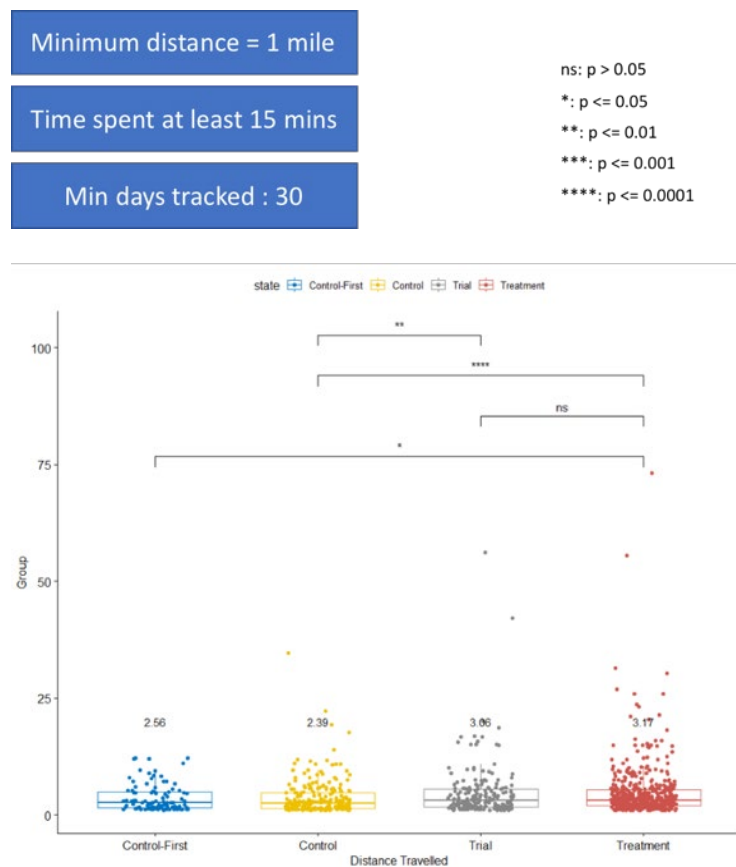
8. Results to Date

One critical question is the impact of our treatment on the geographic mobility of our study participants. While our study provides valuable benefits in the form of up to \$200 of free Uber rides per month for participants in the treatment group, it is not a foregone conclusion that this resource will translate into a

significant increase in the geographic mobility of members of the treatment group relative to members of the demographically similar control group. In principle, our participants could be relatively mobile already, despite their low income and limited access to personal vehicles. If selection into treatment results in only modest increases in geographic mobility, then it would be hard to anticipate an eventual large effect on socioeconomic mobility in either the short run or the long run.

Given that reasonable concern, we report some simple statistical results from the relatively small sample of participants who had been tracked consistently for at least thirty days as of January 11, 2021. We use GPS data to measure average distance traveled, by noting daily locations visited that were at least one mile apart and occupied for at least 15 minutes and measuring the physical distance between them. Each measured distance counts as an observation in our data. We collect these measured distances traveled across the 30 days prior to January 11, and we calculate the group average for the following four categories: 1) individuals in our treatment group, who are receiving \$200 per month in free Uber rides for 6 months 2) individuals in our “trial group” (who are receiving an initial allocation of \$30 in Uber rides to ensure that they can successfully hail and take Uber rides before they transition to treatment or control), 3) individuals in the first month of the control group (“Control First”) treatment arm, who receive nearly as much in free ride credit as members of the treatment group (\$170), and 4) members of the control group in later months, who receive no free ride credits. The statistical tests shown below measure the differences in group means of measured distances.

Fig 3. Differences in Distance Traveled Across Four Groups

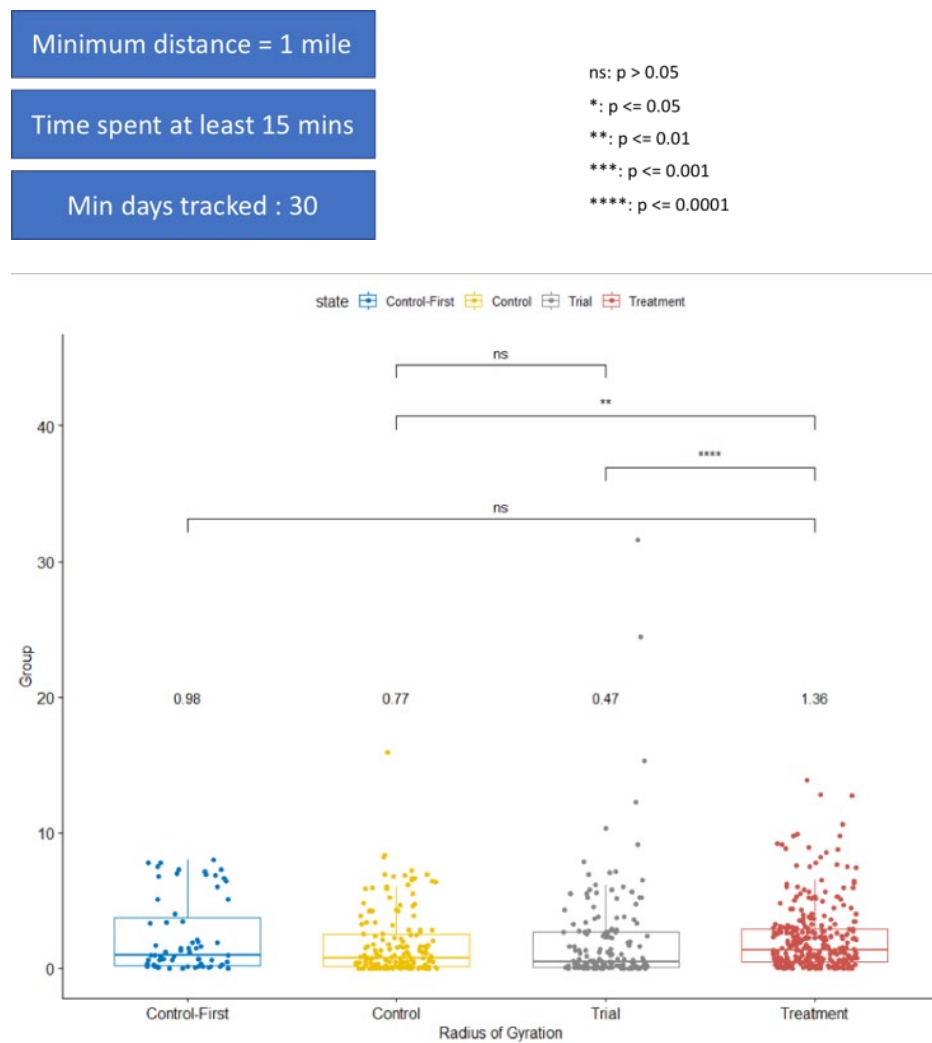


Perhaps the most salient comparison is the difference in average distance travelled between the treatment and control groups. Taken at face value, the results from our admittedly small sample suggest that

members of the treatment group are traveling nearly 33% (one-third) farther than members of the control group. These differences are statistically significant, despite the fact that the samples are numerically quite small, with only 19 individuals in the treatment group and 11 in the control group. As our sample size eventually grows to 650 participants (roughly equally balanced between treatment and control), these comparisons should become more informative.

An alternative, and potentially even more accurate, measure of relative mobility is provided by Figure 4, which measures the average daily “radius of gyration” for each participant in each of the four groups. For each individual, we average the distance between each location at least one mile away from the individual’s modal location (their home) at which they spent more than 15 minutes and their home location over the course of a day. Individuals that travel farther from their homes will record higher daily averages, each of which counts as an observation in our data set. We then take these daily averages for each individual and average them across all individuals who were members of a group during our observation window.

Fig 4. Differences in Average Daily Radius of Gyration Across Four Groups



The differences in measured mobility are even larger than those depicted in Figure 3. Members of the treatment group are 77% more mobile than members of the control group. This difference is significant at the 1% level. We find this measure of mobility more convincing than the previous one, because daily averages within individuals partly control for the fact that different participants have differential access to the internet, keep their phones on for different lengths of time, and therefore send us GPS traces with different frequencies.

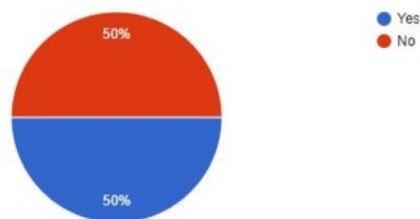
Given the early stages of subject recruitment and the limited number of individuals involved, the absolute magnitudes of the measured differences between treatment and control groups are not something on which we place much emphasis. These measured differences are likely to change substantially as the study progresses and the sample size grows. However, the fact that treatment results in an apparently significant increase in geographic mobility raises our hopes that it could bestow substantial benefits in terms of socioeconomic mobility.

Another important source of data in the early stages of our project comes from monthly surveys. At the time of writing of this report, our sample size is quite small, and survey results should be reviewed with some skepticism. Nevertheless, we share some indicative results from the December 2020 survey of participants in our treatment group, which are illustrated in the figures below.

Figure 5. Participant Employment

During the previous four weeks did you do any work for pay?

20 responses

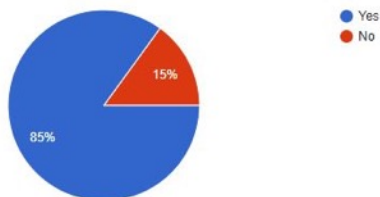


In this small sample, only about half of the participants had worked for pay in the previous four weeks. A solid majority of polled participants were looking for more work opportunities, as indicated in Figure 6.

Figure 6. Participants Looking for More Work

Are you looking for work, either full time or part-time?

20 responses



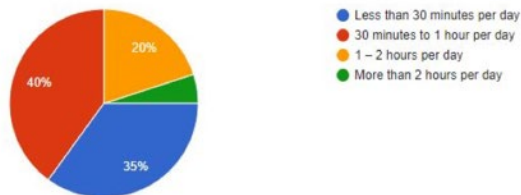
Transportation may be a serious barrier for our target population. Those who worked reported a range of commute times that included ones quite long by Pittsburgh area standards, as noted in Figure 7.

Figure 7. Distribution of Commute Times

On the days you worked last week, about how long did it take you to get to and from work (combined) each day?



20 responses

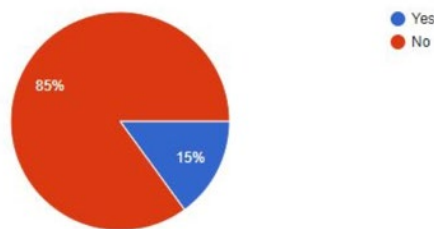


While our study seeks to utilize the additional mobility provided through Uber credits as a means of dealing with barriers to employment, we also recognize that low-income mothers may use the credits to benefit their families in other ways. Figure 8 presents a series of pie charts that illustrate how many participating mothers used Uber credits for a series of objectives not directly related to employment. Note that majorities used Uber credits to provide themselves or their families better access to health care, goods available outside their immediate neighborhood, and recreation opportunities.

Figure 8. Uses of Uber Credits

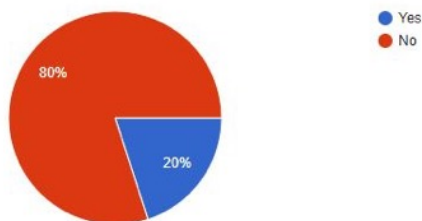
Travel to a court or to appear before a judge in any legal proceedings

20 responses



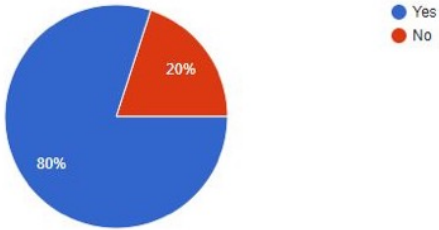
Travel to a training center or community college to receive training or instruction

20 responses



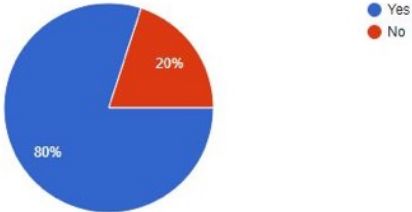
Bring yourself or your children to a doctor, nurse, hospital, or clinic to receive medical or psychological care

20 responses



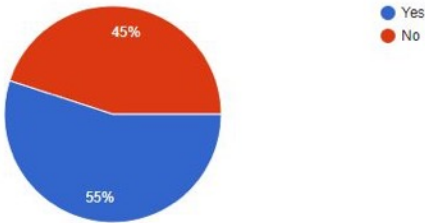
Travel outside your neighborhood to purchase food, clothing, or other items for yourself or your family

20 responses



Take your children to parks, community events, or other activities outside your immediate neighborhood

20 responses

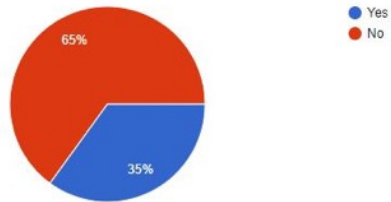


Finally, survey responses shown in Figure 9 make it clear that the COVID crisis has had a significant negative impact on employment opportunities for this vulnerable population.

Figure 9. Impact of COVID on Employment Activities

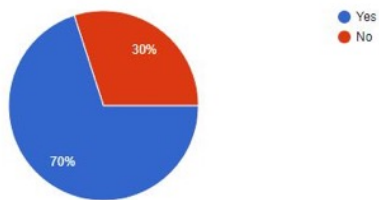
Were you laid off because of the COVID-19 related closure of the business you worked for?

20 responses



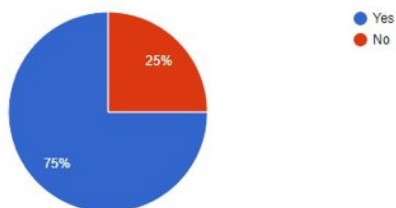
Have you been unable to work (or forced to work less) because of school and/or daycare closures?

20 responses



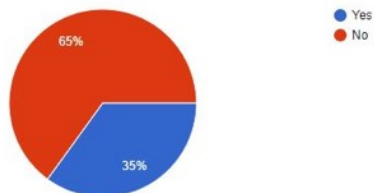
Were your hours reduced because of COVID-19 related closures or partial closures?

20 responses



Has your ability to participate in training or education activities been adversely affected by COVID-19 related closures of schools, colleges, or training centers?

20 responses



9. Scientific Contributions of the Study

Decades of research by economists and other social scientists have pointed to spatial mismatch as a barrier to employment in American cities. Less skilled workers are often concentrated in areas that are geographically distant from the districts where the jobs appropriate to their skill level are being generated in large numbers. Because much of this job creation is happening on the urban periphery, where population density is low and the distances between establishments are high, it can be difficult for less-skilled residents to travel to these jobs if they are wholly reliant on public transportation. Unfortunately, these residents have been trapped for decades between the limitations of public mass transit systems and their own inability to afford cars. Existing transportation technology has offered few alternatives to these two imperfect modes of transit.

Now, however, ride-hailing is diffusing rapidly through American cities, offering a far more flexible and convenient method of transport that does not require private car ownership. As Thebault-Spieker, Treveen, and Hecht (2017) have shown, these ride-hailing services are currently clustered in wealthier districts of American cities, reflecting the reality that the market price points at which these services are currently offered place them out of reach for many of the urban poor. However, targeted public policy interventions could alter this state of affairs. Would subsidized provision of ride-hailing services to the poor enable better access to employment, training, and social services? Could it raise labor force participation, generating social benefits that outweigh the costs? This project seeks to put those questions to a convincing empirical test by conducting a large-scale randomized experiment in the Pittsburgh region. The study will shed light on how a new transportation technology enabled by innovations in mobile computing and machine learning may provide a new solution to one of the most serious social problems American cities have been contending with for decades.

At the same time, the experiment described in this proposal will also address a fundamental limitation in much of the literature that has informed our understanding of spatial mismatch – the nearly complete absence of credible experimental evidence showing that lower transport costs lead to higher labor force participation. Leveraging the emergence of ride-hailing as a new transportation option in the Pittsburgh region, our study will undertake exactly the kind of randomized control trial that has been missing in the literature, and it will exploit the diffusion of smartphones among even the urban poor to track the impact of lower transportation costs on employment and wages. Additional data collected by Allegheny County DHS will provide an important supplement to self-reported data and to the inferences that can be made from the extensive GPS data on participant mobility our study will collect. These data will also help us infer the impact of lower transportation costs on other social outcomes of interest, including utilization of social services. In all of these ways, our study will address important shortcomings in a long literature that has influenced policymakers and social planners for decades.

Finally, we believe that our combination of standard econometric methods, “app” development, and intensive use of smartphones may inspire other economists to expand their tool kits in similar ways. The wide diffusion of smartphones (even among the poor) and the relative ease with which user-friendly “apps” can be created and disseminated have worked together to provide researchers with a new, often low-cost platform through which experimental interventions can be directed and implemented. The same technologies also create important new opportunities for data collection and measurement, often to a degree of granularity and temporal frequency that would have been unimaginable to earlier generations of empirical researchers. While we plan to leverage these technologies to make an important contribution to the literature on spatial mismatch, we think they could be creatively applied to vast range of research and policy domains. As the skill sets – especially with regard to mobile app development -- with which our Carnegie Mellon students are particular well-endowed become more commonplace, it will be increasingly easy for economists and other social scientists to move in this direction.

10. Broader Impacts of the Study

Three decades of research in labor economics document a dispiriting reality – less educated Americans have faced relatively weak demand for their services, stagnant wages, and an increasingly polarized job market (Autor, Katz, and Kearney, 2006). Conventionally measured unemployment is low, but this masks the reality that nearly all of the growth in employment in recent years has been concentrated in high-skill, high-wage jobs or low-skill, low-wage jobs, with weak job growth in the crucial "middle skill" jobs that traditionally offered a pathway into the middle class (Autor and Dorn, 2013). While some of these jobs have been displaced by the rise of imports from low-wage developing countries (Autor, Dorn, and Hanson, 2013), a firm consensus within economics suggests that, over the past generation, the most important force driving this dislocation has been skill-biased technological change, with information technology playing an especially important role in this ongoing exacerbation of inequality.

These dramatic economic and political developments are national in scope, but we see them clearly in Carnegie Mellon's backyard. As residents of the city of Pittsburgh, it is clear to us that the much touted technology-driven renaissance of Pittsburgh has certainly not reached every community in the city, nor is there any reason to expect this outcome without intelligent public policy intervention. Ongoing skill-biased technological change may exacerbate the longstanding geographic inequities within Pittsburgh, and other American cities, that earlier sections of this proposal emphasized. Low-skilled workers in geographically isolated neighborhoods are unlikely to share fully – and perhaps not at all – in the revival of the region, unless intelligent and effective action is taken.

In this proposal, we have laid out a plan to utilize a fundamentally new transportation technology – ride-hailing – which has been enabled by advances in information technology, machine learning, and mobile computing, to provide new opportunities to citizens who are being left behind economically even as this technology enriches the nation and the world as a whole. By using this new technology to enhance the mobility of some of our region's poorest citizens, we can bring a new solution to the longstanding problem of spatial mismatch, potentially helping these citizens connect to better jobs, training, and social services, dramatically improving the lives of their families. The rapid and global diffusion of the ride-hailing business model across the country and around the world means that this new tool exists in many cities. Policy lessons derived from this experiment could be used around the world, potentially impacting the lives of millions.

References

- American Public Transportation Association, (2016), “Shared Mobility and the Transformation of Public Transit,” Research Analysis Submitted by the Shared-Used Mobility Center.
- Fredrik Andersson, John C. Haltiwanger, Mark J. Kutzbach, Henry O. Pollakowski, and Daniel H. Weinberg, (2018), “Job Displacement and Duration of Joblessness: The Role of Spatial Mismatch,” *Review of Economics and Statistics*, 100 (2), 203-218
- David Autor and David Dorn, (2013), “The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market,” *American Economic Review*, 103 (5), 1553-97.
- David Autor, David Dorn, and Gordon Hanson, (2013), “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review*, 130 (6), 2121-68.
- David H. Autor, Lawrence F. Katz and Melissa S. Kearney, (2006), “The [Polarization of the U.S. Labor Market](#),” *American Economic Review Papers and Proceedings*, 96(2), 189 – 194.
- Dan A. Black, Natalia Kolesnikova, and Lowell J. Taylor, (2014), “Why Do So Few Women Work in New York (And So Many in Minneapolis)? Labor Supply of Married Women Across US Cities,” *Journal of Urban Economics*, 79 (C), 59-71.
- Raj Chetty and Nathaniel Hendren, (2018), “The Effects of Neighborhoods on Intergenerational Mobility II: County Level Estimates,” *Quarterly Journal of Economics*, 133(3), 1163-1228.
- John Cogan, (1981), “Fixed Costs and Labor Supply,” *Econometrica*, 49(4), 945-963.
- Kathryn Collins, Erin Dalton, Megan Good, (2014), “Suburban Poverty: Assessing Community Need Outside the Central City,” Allegheny County Department of Human Services Report.
- William H. Frey, (2016), “Melting Pot Cities and Suburbs: Racial and Ethnic Change in Metro America in the 2000s,” Metropolitan Policy Program at Brookings Institution Report.
- Stuart Gabriel and Stuart Rosenthal, (1996), “Commutes, Neighborhood Effects, and Earnings: An Analysis of Racial Discrimination and Compensating Differentials,” *Journal of Urban Economics* 40, 61-83.
- Laurent Gobillon, Harris Selod, and Yves Zenou, (2007), “The Mechanisms of Spatial Mismatch,” *Urban Studies*, 44 (12) 2401-2427.
- Keith Ihlanfeldt and David Sjoquist, (1998) “The Spatial Mismatch Hypothesis: A Review of Recent Studies and Their Implications for Welfare Reform,” *Housing Policy Debate*, 9 (4), 849-892.
- John F. Kain, (1992), “The Spatial Mismatch Hypothesis: Three Decades Later,” *Housing Policy Debate*, 3 (2), 371-392.
- Sara Lichtenwalter, Gary Koeske, and Esther Sales, (2006), “Examining Transportation and Employment Outcomes: Evidence for Moving Beyond The Bus Pass,” *Journal of Poverty*, 10 (1), 93-115.
- Mayer, Thierry, and Corentin Trevien (2017), “The impact of urban public transportation evidence from the Paris region” *Journal of Urban Economics*, 102: 1-21.

McCone Commission Report, (1965), *Violence in the City: An End or a Beginning?* Report of the Governor's Commission on the Los Angeles Riots.

Moeller, J. and M. Zierer (2018). "Autobahns and jobs: A regional study using historical instrumental variables," *Journal of Urban Economics*, 103: 18–33.

Walter Oi, "Residential Location and Labor Supply," *Journal of Political Economy*, 84 (4) S221-38.

Eleonora Patacchini and Yves Zenou, (2005), "Spatial Mismatch, Transport Mode and Search Decisions in England," *Journal of Urban Economics*, 58 (1), 62-90.

Jacob Thebault-Spieker, Loren Terveen, and Brent Hecht, (2017), "Towards a Geographic Understanding of the Sharing Economy: Systemic Biases in UberX and TaskRabbit," *ACM Transactions on Computing-Human Interaction (ACM ToCHI)* 24 (3), 21:1–40.