Expanding Access to the City: How Public Transit Fare Policy Shapes Travel Decision Making and Behavior of Low-Income Riders

by

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Abstract

Over the past five years, as transit fares have been rising faster than inflation, interest in establishing programs providing discounted public transit fares to low-income individuals has blossomed in the US . Limited research exists, though, on how affordability of the fare influences travel behavior, and affects access, to destinations such as healthcare, and, ultimately, quality of life. This hampers efforts by policy makers and advocates to evaluate the potential for means-tested fare programs as an intervention to ameliorate the impacts of transit costs. This research aims to answer the following questions: 1. How do travel patterns of low-income transit riders differ from those of average riders? 2. What is the causal effect of a fare subsidy on the number of trips taken by low-income riders? 3. In what way does transit cost impact healthcare utilization for low-income individuals? 4. How do low-income transit riders decide whether to purchase a pass or pay for trips individually?

50% fare subsidies cause an increase of 2.3 trips per week (27%), equivalent to a fare elasticity of -0.54. There is a statistically significant treatment effect on trip rates to healthcare appointments, and evidence from the interviews suggest that trips for regular maintenance visits for chronic conditions are the type of healthcare visits likely to be forgone because of an inability to afford the transit fare. I found that *scarcity mindset*, the behavioral economics theory which suggests that living in poverty impedes cognitive capacity, is not universal among low-income individuals. I also found that 30% of individuals paying for trips individually would have received better value by purchasing a pass product. Low-income riders take proportionally more off-peak trips, and African Americans have longer commutes even controlling for income.

A major policy implication of this research is that means-tested fare programs will provide tangible benefits to its recipients because the cost of public transit has been shown to limit mobility of low-income residents. This research also suggests that healthcare providers should be proactive in providing free public transit for patients. Next-generation fare collection systems will open the door for innovative collaboration with other social service agencies. The findings in this dissertation inform the future of public transit fare policies. Finally, with evidence of travel time disparities by race, structural causes must be addressed.

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Contents

1 Introduction

This dissertation is motivated, in part, by recent growth in income and wealth disparity and racial inequalities that remain unmitigated. 20% of national income in the US now goes to the top 1% compared with 10% in 1980 (Pew Research Center, 2016). There is lack of agreement on the fundamental causes of inequality and its effects on society, and the tradeoffs associated with economic growth. Some argue that income inequality leads to unequal access to opportunity and resources, decreasing the chances of escaping poverty and limiting the upward mobility of the middle class (Mishel, Bivens, Gould, & Shierholz, 2012). But others suggest that inequality is not inherently bad, in that it motivates economic growth which benefits people at all income levels even if many receive a smaller overall slice of the resulting benefits (Davis & Moore, 1945). Whether good or bad, some economists believe that inequality naturally declines as capitalism matures (Kuznets, 1956), while others disagree. The economist Thomas Piketty (Piketty & Saez, 2014) claims that, "market forces and capitalism by themselves are not sufficient to ensure the common good and to limit the concentration of wealth at levels that are compatible with democratic ideals." Current debates in economics, social sciences, and policy making are enlivened by questions surrounding what should be done and who bears the responsibility to act.

Transportation is one aspect of urban inequality that has recently garnered significant attention, especially the role of public transit in the lives of those with limited economic means who live in dense urban cities (Garrett & Taylor, 1999). The affordability of transportation has long been a discriminator regarding access to the benefits urban society has to offer. Accessing needed goods, services, and activities allow for the fulfillment of life's basic physical and social needs. The US social safety net includes support for housing, food, and healthcare but not transportation yet, transportation is considered a critical factor enabling access to jobs and other services (Sanchez, Stolz, & Ma, 2004). Current methods for appraising the benefits of transit on underserved populations do not sufficiently capture the social dimensions of mobility and accessibility (Lucas, van Wee, & Maat, 2016). Those with limited economic means rely more heavily on public transportation since they are disproportionately poorer than those who drive (Brian Taylor & Morris, 2015), the assumption being that public transit is more affordable than owning and operating a personal vehicle. Acknowledging the poor quality of public transportation in most urban areas in the US, academics have previously focused on lack of vehicle ownership as a barrier to improved quality of life (Wachs, 2010). While appropriate for suburban areas and sprawling metropolitan areas with poor public transit, this approach is less applicable to compact cities with robust transit systems where it is far more feasible to utilize public transportation for most mobility needs. Academics continue to debate whether affordability is the barrier or aspects of service such as quality, reliability, frequency, schedules, or access to desired destinations (Cervero, 1990).

With transit fares rising faster than inflation, income inequality growing, and social justice causes gaining traction, planners and advocates are now focusing attention on affordability of the fare as a potential barrier to access (Mallett, 2018). In the US, household expenditures grew and income dropped in the decade following the Great Recession from 2004 – 2014. By 2014, median income had fallen by 13% while expenditures increased by 14%. The rapidly growing cost of housing in many cities over the past decade is a major contributor. Lower-income household expenditures on transportation went from 9% of household income in 2010 to 16% in 2014 (Pew Research Center, 2016). Transit fares in Boston have doubled from 2000 to 2018 accounting for inflation. In response, interest in programs to provide discounted public transit fares to those most marginalized in society has grown over the past five years (Moffitt, 2018). Prior to 2015, San Francisco's *Lifeline* discounted monthly bus pass was the only means-t ested fare program in the US and it garnered little national attention. Seattle's 2015 *ORCA Lift* discounted fare program, though, pushed the issue into the public spotlight nationwide (Johnson, 2015). In Boston, means-tested fares entered the public discourse in late 2015 with the publication of an opinion article in the Boston Globe (Leung, 2015). Government agencies and advocates are now debating the merits of implementing such programs but have little research on which to base their assessments. There is limited research on the impact of fares on the ridership specifically of low-income individuals (McCollom & Pratt, 2004) and, by extension, the impact on their livelihoods (P. Jones & Lucas, 2012). Studies conducted over the past several decades take advantage of fare increases as "natural experiments" to estimate elasticity of demand. These studies rely on small fare increases and rarely assess the impact specific to low-income riders. In addition, no existing research quantifies the impact of larger fare reductions, such as a 50% discounts, on low-income rider behavior. The limited evidence-based research on the benefits of such programs, though, is a barrier for policy makers when they seek to evaluate and potentially prioritize such programs. The intent of this dissertation is to help fill gaps in this research so as to contribute to the evidence upon which policy decisions can be made.

1.1 Research questions

The overarching research agenda was to better understand the travel needs and behaviors of low-income transit riders in order to help policy makers assess the potential value of means-tested public transit fare discount programs. I took a mixed-methods data collection approach to address four specific research questions. The quantitative approach involved a real-world randomized controlled evaluation experiment and the qualitative approach involved interviews with study participants. The four research questions, along with their associated hypotheses and methodological approaches, are presented in Table 1.1. More details on the research questions are provided below.

Table 1.1 Research questions, hypotheses, and methods

Research questions	Core hypotheses	Methods
1. How do travel patterns of low-income transit riders differ from those of average riders?	Low-income riders take proportionally more off-peak trips. Income, and not race, correlates to travel time.	Descriptive statistics
2. What is the causal effect of a fare subsidy on the number of trips taken by low-income riders?	Fare subsidies increase the number of transit trips taken. Both necessary and discretionary trip types are impacted.	Randomized controlled evaluation
3. In what way does transit cost impact healthcare utilization for low-income individuals?	Healthcare trips for chronic conditions are the type likely to be forgone.	Semi-structured interviews
4. How do low-income transit riders decide whether to purchase a pass or pay for trips individually?	Individuals prefer to pay per ride because of lower up-front cost, but at the expense of increased stress and forgone trips.	Semi-structured interviews

⁂ ⁂ ⁂

(1) How do travel patterns of low-income transit riders differ from those of average riders?

Mobility patterns of low-income individuals compared with the average population is poorly understood, largely resulting from data that is not able to be segmented by income. Resource-intensive passenger surveys are one source, though often are limited because of low respondent numbers or lack of representativeness (Schaller, 2005). National Household Travel Survey data, useful for high-level national trends, does not provide fine-grained city-level information. US Census data does not provide pre-tabulated products for income and commute-to-work mode. Researchers often associate average demographics of detailed census tracts with boardings at nearby transit stops, but this approach has limitations (Karner, Kuby, & Golub, 2015). Lastly, *Big Data* from transit agency smart cards is not helpful for understanding low-income rider behavior because user demographic information cannot easily be associated with individual smart cards. Segmentation analyses can be conducted to differentiate travel behavior of seniors and persons with disabilities because of the application process required to obtain those cards. As a last resort, Data regarding seniors and persons with disabilities are often used as a proxy for low-income individuals, but are poor substitutes.

I take three different approaches to identify ways in which travel patterns of low-income transit riders differ from average riders using descriptive statistics derived from several data sources. First, I obtained and analyzed the raw records from the latest MBTA passenger survey to investigate differing mobility patterns of low-income and minority riders, such as the number of trips taken, modal split between bus and subway, and household car ownership. This dataset has not yet been mined for insights into differential travel behavior based on income. Secondly, I compared the dataset of smart card usage generated by the low-income population in my study with smart card data of all MBTA riders to identify differences in time-of-day travel, an issue that is poorly documented yet has important implications for fare policy. The hypothesis is that low-income riders take a higher percentage of their trips during off-peak hours, information not currently available from the MBTA's automated fare collection system. Finally, I used the American Community Survey Public Use Microdata Sample data, a set of untabulated census records, to investigate how commute time correlates based on race and income. A previous study concluded that race correlates with travel time but did not correct for income (Pollack, 2012) leading me to hypothesize that income is the true correlate to travel time, not race (I found the opposite to be true: race correlates with travel time irrespective of income.)

* * *

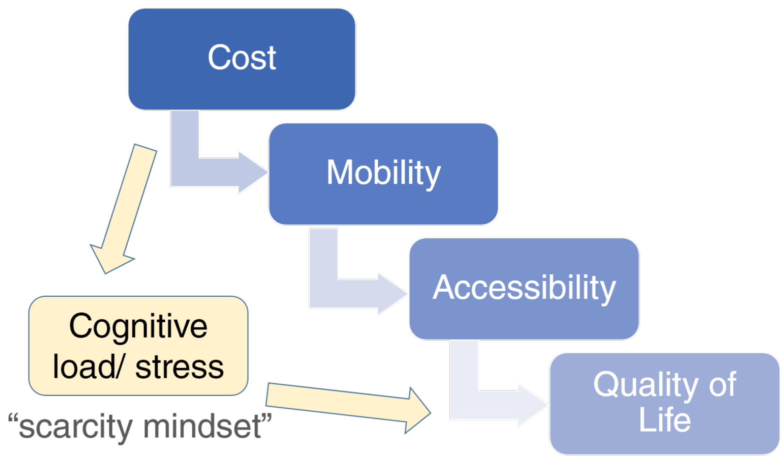
(2) What is the causal effect of a fare subsidy on the number of trips taken by low-income riders?

To address this question, I designed and implemented a randomized controlled evaluation experiment. This methodology has seen rapid growth in social science research as it can accurately determine the impacts of social interventions by eliminating confounding factors (Angrist & Pischke, 2014). Alternatives, such as econometric or qualitative approaches, do not provide the same level of confidence in the results because of the problem with lurking confounders. A well-run randomized controlled evaluation can successfully isolate the specific intervention of interest from the multitude of possible other covariates allowing researchers to draw causal conclusions. To test the effect fare subsidy programs have on the level of mobility and access, I conducted a real-world randomized experiment on a sample of 242 transit riders in the Boston area who receive food subsidy benefits. Half were randomly selected to receive a special smart card that automatically provided a 50% discount (the treatment group) while the others were provided a standard smart card (the control group). The study was conducted from January 2019 to June 2019. Each participant was engaged in the study for a two-month period. Boston was selected as the case site location because of its suitability for a low-income fare program and because of the willingness of the transit agency, the Metropolitan Bay Transportation Authority (MBTA), to collaborate. In order to run the study in real-world conditions that would exist if a low-income fare program was implemented, special smart cards for treatment group participants needed to automatically provide a discount in real time. Reimbursing participants after the fact would likely impact participant behavior by removing the instant discount feature.

With long-term effects of policy interventions difficult to measure, researchers resort to shorter-term intermediary metrics that can be more easily operationalized and measured over a shorter period of time. Relying on existing theory, assumptions are then made on the expected downstream effects. For social safety net interventions such as discounted transit fares, the policy objective is to improve recipient outcomes, such as income, health, and quality of life. My hypothesis is that transit cost is a barrier and that a low-income fare will increase the number of trips taken. If a reduction in transit cost does increase the number of transit trips taken by low-income individuals, then it is assumed that that increased access to important goods and services will follow, which is then assumed to improve quality of life outcomes.

This causal pathway framework is shown in Figure 1-1 (the *scarcity mindset* pathway is addressed with question 4 below). The randomized controlled evaluation operationalized the concepts of both *mobility* and *accessibility* as dependent variables. Mobility was represented by the number of transit trips taken as reported by smart card data. To measure accessibility, trip rates for different trip purposes were determined from data reported by participants to the travel diary, thereby illuminating whether certain types of trips, such as work, healthcare, training, visits to family, or shopping, are more sensitive to the cost of public transportation. Although some evidence suggests that discretionary trips are more likely to be forgone because of cost, this has not been rigorously studied (Perrotta, 2017). My hypothesis is that both necessary and discretionary trip types are impacted by a fare subsidy. Because of the large number of zeros in the count data for number of trips taken in different categories, a zero-inflated negative binomial regression model was used to further investigate the treatment effect.

Figure 1-1 Causal pathway diagram



* * *

(3) In what way does transit cost impact healthcare utilization for low-income individuals?

Improving the health of low-income individuals is an important policy objective, especially because income correlates highly with health risk factors such as higher rates of heart disease, stroke, diabetes, obesity, hypertension, or physical limitation (Center for Health Statistics, 2012). Health literature points to maintenance visits for chronic illness as an important correlate to better health outcomes, especially for low-income individuals, because chronic illnesses can quickly destabilize causing significant long-term health impacts (NCHS, 2017). It is likely that individuals prioritize acute healthcare needs differently from regular routine maintenance visits for chronic illnesses, but this issue has received minimal research focus in the transportation field. My hypothesis is that when transit cost is an issue, individuals are more likely to forgo healthcare trips for chronic conditions, but not for acute illnesses or emergencies. Participant interviews were used to illustrate the impact of transit affordability on access to healthcare.

* * *

(4) How do low-income transit riders decide whether to purchase a pass or pay for trips individually?

Low-income riders can be disproportionately impacted by transit fare policies. How they choose to pay for fares, or otherwise compensate, is poorly understood. For example, it is known that larger up-front cash outlays for monthly passes are challenging and as such, low-income individuals may not get the best value over the course of the month (Barajas, Chatman, & Agrawal, 2016). How a low-income fare product is implemented is likewise important- providing only discounted monthly passes or including discounting pay-per-ride in the program may have important ramifications on the travel behavior of and financial benefits for low-income riders. There are also new considerations on the horizon. Recent technological improvements in transit fare collection systems have opened up possibilities for innovative fare products such as *fare capping* where customers pay for each trip individually but when a certain payment threshold is reached within a designated time period, subsequent trips in that period are automatically free (K. Taylor & Jones, 2012). The concept of *mobility as a service* (MAAS) is another, whereby transportation payments for various modes including public transit may be bundled together (Buehler, 2018; Watkins, 2018). To ensure equity is part of the policy development process, a better understanding is needed regarding how low-income riders make fare payment decisions.

To better understand how low-income riders make payment decisions, I incorporated theories from behavioral economics literature. Recognizing that people do not necessarily make what would appear to be logical, rational decisions, transportation researchers are turning to behavioral economics approaches. In the context of studying people living in poverty, these theories and insights have proven useful in better understanding how living with scarcity influences cognitive capacity. Referring back to Figure 1-1, there is also a pathway linking the stress of poverty with diminished health outcomes (Selye, 2013). An assumption can then be made that relieving stress associated with paying for transit or making individual trip decisions will lead to improved health outcomes. In order to better understand the sources of such stress, I propose a two-tier process to describe how purchasing and traveling decisions are made: first whether or not to purchase an unlimited weekly or monthly pass product, and second, if a pass is not purchased, whether or not to take each individual trip. I focused my analysis on how people made the decision to purchase a weekly or monthly pass or to pay for transit trips on an individual basis.

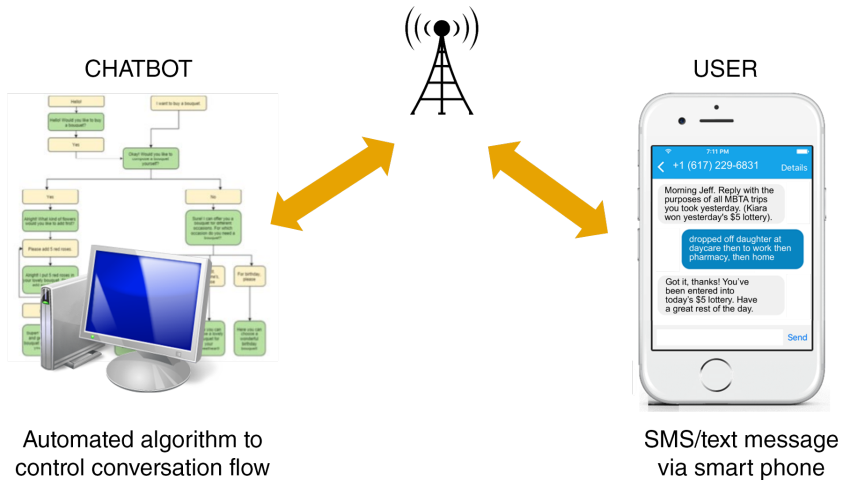
My hypothesis is that low-income individuals prefer to pay per ride because of lower up-front cost, resulting in forgone trips and increased stress. For this investigation, I used a combination of smart card usage data and participant interviews. Smart card data revealed how each participant chose to manage each transit payment over the study period and the interviews provided insight into the thought process. A unique feature of this analysis is that for each participant interviewed, I was able to cross reference observed payment behavior with that individual's perspectives.

* * *

ChatBot tool

The ChatBot tool itself is a contribution of this research project. With the high penetration rate of smartphones, even among low-income populations, researchers have recently turned to these devices as tools for data collection. Custom designing apps is challenging. It involves accommodating various devices, screen sizes, and operating systems, programming a robust user interface, and ensuring reliability and robustness. Users are often reticent to download third-party apps because of limited storage space, battery drain, and privacy concerns (Hoch, 2015). Low-income individuals pose additional challenges because they have less consistent internet connectivity than average smartphone users (Smith, 2015). For these reasons, I opted for a text/SMS messaging platform as an alternative to a smartphone app (Figure 1-2). While there are many examples of the use of text messaging by health intervention programs, political campaigns, and in international development contexts, there are limited examples of its use to engage participants in other research. I custom-designed a ChatBot tool to automate participant recruitment as well as collect daily travel diary information from the participants. I was granted permission by MIT's Institutional Research Board to obtain participant consent via text message rather than paper signature, thereby reducing a significant barrier to enrollment rates. Programming the ChatBot was far simpler than for a custom designed app and the cost associated with the SMS interface with the cellular network was low. There was a very high response rate to the daily ChatBot diary, with participants responding to the daily ChatBot text requests an average of 73% of the time. Following successful implementation for my research, the ChatBot tool has been adopted by multiple other research teams: a Notre Dame research team utilized it in a study evaluating the impact of free-fares in Seattle, and a researcher at MIT, in collaboration with the Boston Redevelopment Authority, deployed it in a study involving housing vouchers.

Figure 1-2 ChatBot interacts via text/SMS messages with participants' mobile phones



1.2 Dissertation outline

The dissertation is organized as follows. Chapter 2 situates the concept of means-income fares within historical and theoretical contexts. Attention is focused on relevant changes that have occurred throughout the twentieth century: the declining role of public transit in urban mobility, shifting priorities for the social safety net and welfare, and maturing conceptualizations of equity and justice.

Chapter 3 details the research design for the project. I explain the rationale and architecture for the randomized controlled evaluation experiment, selection of Boston as the case site location, estimation of the necessary sample size, recruitment of participants, use of MBTA smart cards that automatically provide discounts to the user, design and use of the automated texting ChatBot tool for recruitment and daily travel diary data collection, execution of the experiment, and design of the semi-structured participant interviews. I briefly discuss how I overcame various political and legal challenges in order to successfully collaborate with the necessary government agencies.

Chapter 4 provides descriptive statistics for travel behaviors of low-income transit riders utilizing data from three sources: MBTA's automated fare collection system, the latest MBTA passenger survey, and US Census micro-data. Characteristics include mode choice (bus vs. subway), automobile ownership, payment method, time of day travel, transfers, commute time, and ridership based on age and minority status. Results indicate that low-income transit riders take more off-peak trips, make twice as many transfers, and are far more likely to live in zero-car households. African American transit riders have longer commutes regardless of income and mode.

Chapters 5 through 7 present results from the quantitative and qualitative components of the study. Chapter 5 presents the findings from the randomized controlled evaluation. The average treatment effect was calculated as the difference in the average number of trips taken by the control and treatment groups. Results indicate that receiving the transit discount caused an increase of 2.3 trips per week, equivalent to an elasticity of -0.54. The travel diary coding methodology and results of the trip purpose analysis are then presented. Of all of the trip purpose types, I only found a statistically significant treatment effect on healthcare trips. Chapter 6 provides a more in-depth investigation into transit barriers to healthcare access. Results from the zero-inflated negative binomial regression analysis are presented. The only finding is that higher self-reported health rating correlates with the reporting of zero healthcare trips. The second part of the chapter draws on the qualitative interviews to investigate healthcare trips for chronic versus acute health issues. There is evidence from the interviews that routine visits are the types of health-care appointments that are occasionally skipped, and that affordability of transportation is a factor. Six interviews are presented as case studies to highlight contextualized examples of the variety of different decision making behaviors observed.

Chapter 7 takes a behavioral economics approach to examining how low-income individuals choose to pay for transit. A two-tiered decision making framework is presented whereby an initial decision of whether to purchase a weekly or monthly pass has a down-stream effect on the need for affordability deliberation on a trip-by-trip basis. There is evidence that trips are forgone when paying on a per-trip basis. In addition, there is evidence that behavior falls into two archetypes: *attentive* and *inattentive* planning. This suggests that the *scarcity mindset* theory, that poverty itself causes diminished executive function, short term thinking, and difficulty coping with shocks, is not universal among low-income individuals. A combination of interview results and analysis of smart card purchasing and use patterns for individuals is used to support this finding. Regarding payment method, I found that 30% of individuals in the study who chose to pay for trips individually would have received better value by buying a pass product- a surprising result considering that one would expect that low-income individuals would have higher incentive to "get the better deal." I conclude by suggesting policy implications that are somewhat counter to prevailing wisdom regarding the benefits of *fare capping*, arguing that offering means-tested fares to pass products only, and not pay per ride, would nudge low-individuals to purchase the unlimited pass product which would be beneficial by removing the stress of the pay-per-trip decision making element.

I conclude the dissertation in Chapter 8 with a summary of the key findings along with a discussion of the public policy implications of the research and some limitations of the study. I then present several potential ideas for further exploration.

2

Literature review

This chapter reviews what is already known about travel behavior of low-income transit riders, with a focus on affordability. I start with a brief summary of urban history over the past century or so highlighting several threads that help explain where we are today: first the decline of public transit that accompanied the rise of automobility; second, urban planning policies that led to economic disparities along spatial and racial lines that still manifest today; and third, institutional manifestations of the provision of welfare. I continue with a review of how scholars position transportation as an important factor in the quality of life outcomes of low-income individuals and the efforts of planners to ameliorate transportation barriers. A summary literature on public transit affordability literature is also provided. The final section introduces the concept of accessibility as a better metric to assess public transit than simply mobility.

Transportation is a critical factor for how cities are shaped. Cities provide advantages that offset the disadvantages: spatial agglomeration reduces transport costs, increases exchange of ideas and goods, and benefits capitalism by situating consumers and workers in close proximity (Glaeser, 1998). Over the last two centuries, we have seen innovations in transportation technology that have significantly altered our urban fabric. Following the industrial revolution and the deployment of the railroad network, mass transit became a primary urban transport mode. From 1890 through 1950, mass transit, such as train, subway, trolley, and bus, dominated urban travel, with very high levels of per-capita ridership. Its decline came alongside the rise of automobility (D. Jones, 2008). A 1956 publicity film claimed: "to be fully dynamic, the American city must now accommodate the automobile. This is the vital factor of our new age. The forward-looking city is conscious of the automobile and automobile traffic as key factors (Baskaw, 1956)." The rise of the automobile, starting in the 1920's, through the interstate highway era, starting in the 1950's, led to a cycle of significant decline in transit service with ridership plummeting from 160 average trips per capita per year in 1950 to 36 in 1970 (APTA, 2019). The rapid increase in driving simultaneously reduced ridership and added to roadway congestion making streetcars painfully slow and even less attractive (Norton, 2011). This led to the bankruptcy in the 1960's of transit systems across the US which were, at the time, privately owned but regulated by government. Pointing to market inequities and unacceptable externalities, government intervened. The predominant public perception became that public transportation is a government aid program to help poor people who lack cars, not something that benefits the middle class (Seiler, 2008).

Transit system ownership in US cities was transferred to public authorities with significant encouragement and financial incentives from the federal government. The 1964 Urban Mass Transportation Act, signed by President Lyndon Johnson, increased federal involvement in transit by providing grants for public takeovers of failing private transit companies, as well as for additional capital investments. In 1974, the National Mass Transportation Assistance Act marked the beginning of a decade of increased federal funding of transit operating costs for agencies across the US (Thompson, 2008). These programs emphasized rail service and included, for example, the construction of the Metro in Washington, DC and the expansion of subway and commuter rail service in the Boston region. With the shift to a neoliberal policy outlook in the 1980's Reagan era, government support for transit declined, leaving transit systems drastically underfunded. By 2000, most systems had such a large backlog of deferred maintenance that decreases reliability and service quality reached crisis proportions (D. Jones, 2008). Buses, relied upon more heavily by low-income riders, received even less attention than subways and streetcars (Garrett & Taylor, 1999).

2.1 Equity

Much of the literature on transportation equity posits that historical urban planning policies were an important factor leading to the levels of racial segregation and spatial inequality, as well as transportation inequities, we see today (Gössling, 2016). In the early 1930s, a governmental organization called The Home Owners Loan Corporation began the practice of *redlining* which deemed certain neighborhoods (not coincidentally ones where a majority of the residents were non-white) a financial risk, thereby denying mortgage loans (Rothstein, 2017). While many progressives look back with fondness at the New Deal with its "freedom from want," some warn against overly romanticizing that period. Scholar Jennifer Mittelstad (2015) argues that, "the New Deal was part of a hodgepodge of varied and sometimes hidden social welfare programs- some public, some private- that rewarded different groups of Americans for different reasons...Though its programs enveloped a wider swath of citizens over time- more non-whites, more women, and more marginal workers- their entrance into the safety net was hard fought and politically controversial." Next came the GI Bill in 1944 which guaranteed subsidized mortgages to returning servicemen after World War II, but was structured in a way that allowed bankers and new suburban developments the ability to block African Americans from becoming homeowners. In New York and northern

New Jersey suburbs, for example, only 100 of the 67,000 GI Bill mortgages were provided to non-whites (Katznelson, 2005).

Further contributions to racial segregation came from large-scale urban renewal projects starting in the 1950s that targeted predominantly black urban communities. Under the auspices of solving urban blight problems via slum clearance, these programs were to provide public housing for those displaced, though only a small fraction actually received new housing (Caro, 1974). James Baldwin (1989) referred to urban renewal as "Negro Removal". Failures of urban renewal to reduce poverty or improve the lives of the poor were in part responsible for the riots and social unrest and civil rights activism in the 1960's. In response, studying poverty and unemployment became a focal point for many academics and urban planners (Metzger, 1996). Anti-highway movements in many US cities successfully opposed impending incursion of highways into the urban centers, which would displace the poorer and non-white segments of the population (Crockett, 2016). Public transportation has long been at center stage for social struggles at equality. In the US, the 1955 bus boycott in Montgomery and the 1961 Freedom Riders campaign are important historical markers of the Civil Rights movement. Today, there is growing interest in going beyond removing barriers so as to level the playing field, as reparations for past injustices (Coates, 2004). This resonates with many transportation advocates who are asking for renewed transit investments in their communities to compensate for past neglect (Bullard, 2004; Golub, Marcantonio, & Sanchez, 2013).

In identifying root causes of poverty, the 1965 "Moynihan Report," officially titled *The Negro Family: the Case for National Action* (1965), popularized the concept of the "the culture of poverty," a term previously coined by Michael Harrington in his 1962 book *The Other America* (1962), that suggested individual character flaws were the root cause of poverty. Moynahan described it as a "tangle of pathology," which including delinquency, joblessness, school failure, crime, and fatherless children. Others placed blame on the "deterioration of the Negro family" (Greenbaum, 2015). This public perception had the effect of policy makers and politicians turning attention away from the structural causes of poverty. White resentment of black Americans continues to be one of the central forces behind opposition to traditional welfare which provides aid to low-income families with children (Geary, 2015). Any conversation today about equity in an urban planning context must take this history into consideration. In this research, I recognize that a low-income fare program is not necessarily addressing the underlying structural causes of poverty and inequality so should not be considered a substitute for such work.

2.2 US welfare policy

Welfare theory had its beginnings in the late 18th century with Thomas Paine (1771), who advocated for a strong federal government, criticized economic inequality and poverty, and proposed the world's first fully fleshed-out scheme of social welfare provision. "When in countries that are called civilized, we see age going to the workhouse and youth to the gallows, something must be wrong with the system of government." Paine was considered ahead of his time as the welfare state did not come into existence until a century later. Instead, in the early nineteenth century, English Poor Laws were, in essence, primitive and harsh welfare programs administered by religious parishes. Following reform of the Poor Laws, welfare provision in Europe and North America was generally seen as the responsibility of charity from the private sector (Trattner, 1999). It was not until post World War I that modern welfare programs began, starting with the New Deal in the 1930's, which introduced Social Security, protections for unionized labor, and financial support for the significant number of unemployed. The next wave of welfare programs included Great Society programs in the 1960's which addressed poverty alleviation and racial injustice. The subsequent Reagan/Thatcher era of the 1980's began a period of welfare retrenchment. Previous expansive social policy of *welfare optimism* turned to one of *welfare pessimism* (Taylor-Gooby, 1997). An important development was a shift in the conceptualization of welfare recipients in the public discourse from the "deserving poor" to the "undeserving poor" (Katz, 1990). The term "welfare queen" became a popular political trope during that era to claim that black, single mothers were responsible for rampant abuse of the system (Petridou, 2014). The political scientist Wendy Brown (2019) suggests that the "demonization of public goods is the fruit of the neoliberal program, as it was rolled out here and in Europe in the 1980's, which aimed to discredit the social state, and with it, all universal programs as both inefficient and morally wrong." Suzanne Mettler, in *Government-Citizen Disconnect* (2018), points out how saliency factors into the political process, "but partly because of policy design—which makes means-tested programs for the poor more visible than policies for the rich hidden in the tax code—many Americans don't recognize the value of government social programs." The arrival of the 1996 *Personal Responsibility and Work Opportunity Reconciliation Act* (otherwise known as Welfare Reform) by President Clinton predicated aid on strict work requirements and placed a lifetime cap on benefits.

How to allocate welfare benefits is a fundamental question with economic, political, and moral implications. Scholars see a trade-off between targeting and universalism. Some argue that targeting is the more efficient approach (Jacques, 2018), while others emphasize the negative political consequences of such an approach (Pierson, 1995). Sociologists Walter Korpi and Joakim Palme (1998) argue, "by discriminating in favor of the poor, the targeted model creates a zero-sum conflict of interests between the poor and the better-off workers and the middle classes who must pay for the benefits of the poor without receiving any benefits...The greater the degree of low-income targeting, the smaller the redistributive budget." An alternative is to distribute government aid across as wide a population as possible, such as through universal basic income programs, which may be more effective at poverty alleviation (Wispelaere & Noguera, 2012). Programs such as Social Security and Medicare, which go to everyone over a certain age are the closest thing to universality in the US. Some view public transit as having the potential to be universal, providing *access for all* (Schaeffer & Sclar, 1975). Sufficient urban density and mixed-use development combined with good public transit provides for equitable access regardless of socioeconomic status. Some scholars, taking a capabilities approach, suggest setting a minimum standard of accessibility to key destinations (Pereira, Schwanen, & Banister, 2017).

Much of the social safety net for the most vulnerable groups in the United States is characterized by highly fragmented programs administered in a piecemeal fashion with separate bureaucracies and their associated arduous procedures and requirements (Bruch, Meyers, & Gornick, 2018; Michener, 2018). The five largest means-tested transfer programs are food subsidy (SNAP), Temporary Assistance for Needy Families (TANF), Supplemental Security Income, housing benefits through HUD, and the Earned Income Tax Credit (EITC). They are all highly targeted with different thresholds of participation. In contrast, the social safety net in the Netherlands, for example, provides a single cash benefit transfer at a subsistence level for those who cannot support themselves, and it has all safety net services provided by the same agency (Steffens & de Neubourg, 2007).

Many in the US take advantage of some aspect of the social safety net over the course of their lives. About half of Americans will experience poverty at some point before they reach 65, and 75% of people will have emerged from poverty within four years. That still leaves 25% who don't get out quickly. Statistically, the longer an individual stays in poverty, the less likely it becomes that they will ever get out (McKernan, Ratcliffe, & Cellini, 2009).

With increased cost of living coupled with decreased earnings, there is evidence that welfare payments do not meet the needs of many individuals, forcing them to seek supplemental income. One study found that on average, welfare, food stamps and Supplemental Security Income only covered approximately 60% of expenses. 75% percent of recipients received unreported contributions from their personal networks and 30% received direct assistance from a community group. This makes the pressure for meeting the welfare work requirement challenging, and can be considered a failure of the labor market (Edin & Lein, 1997).

There are conflicting views on the responsibility of society for those at the margins. Stiglitz (2012) suggests that inequality affects those who are well off so takes a broader social welfare approach: "paying attention to everyone else's self-interest – in other words to the common welfare – is in fact a precondition for one's own ultimate wellbeing… it isn't just good for the soul; it's good for business" (p. 288). Others suggest a moral underpinning, such as the Right to the City movement. In this context, public transportation is a symbol representing what is good about a city and suggests transit should be a *right* for the poor. Such an approach is in alignment with theorists who push for a more *just city* (Fainstein, 2000; Harvey, 2008; Marcuse, 2009). In referencing Marx and Engels, the urban scholar Kafui Attoh (2017) sees "the struggles over urban transportation as struggles over the political possibilities of cities themselves... Public transportation not only matters for who is part of the public, but for securing a right to the city" (p. 197).

The environmental justice movement addresses the issue that communities with poor transportation access are often also burdened with the environmental effects of transportation infrastructure such as bus depots and highways (Agyeman, 2005). Somerville, Massachusetts, for example, has poor public transit connectivity compared with neighboring municipalities, while the highway cutting through it is the cause of increased asthma rates among nearby inhabitants (Fuller et al., 2013). Environmental justice concerns bolsters the argument that underserved communities deserve increased attention.

The meaning of inequality, and how to address it it, is highly contested, as illustrated by this quote of Josha Rothman (2020): "the blurry nature of equality makes it hard to solve egalitarian dilemmas from first principles. In each situation, we must feel our way forward, reconciling our conflicting intuitions about what 'equal' means. Deep equality is still an important idea— it tells us, among other things, that discrimination and bigotry are wrong. But it isn't, in itself, fine-grained enough to answer thorny questions about how a community should divide up what it has. To answer those questions, it must be augmented by other, narrower tenets." Currently, the equity policies of most transit agencies in the US consist only of the required federal Title VI disparate impact/ disproportionate burden analyses designed to limit further harm to protected classes of people (namely people of color) or the poor. When applied to fare increases, though, only horizontal equity is taken into consideration – *unfairness* exists only if there is more than a 20% difference in the percent of minorities impacted compared with the overall population (Karner & Golub, 2015).

2.3 Mobility as a social good

While transportation is, of course, important for everyone, equity planning focuses attention on the needs of underrepresented constituencies, notably those at the lower end of the economic spectrum (Krumholz & Forester, 1990; Reece, 2018). When adequate transportation is viewed as fundamental to enable improvements in economic and health outcomes, it is surprising how relatively little attention it receives. Inadequate access to destinations that provide jobs, services, and recreation leads to poorer individual well being as defined by economic, health, and social indicators. Much of the literature focuses on transportation barriers to employment outcomes. Many correlate automobile ownership with improved employment outcomes arguing that public transit is simply inadequate (Ong & Blumenberg, 1998; Waller, 2005). One study has shown that households without vehicles have lost income over the past half century, both in absolute terms and relative to households with vehicles

(King, Smart, & Manville, 2019). Another study of lower-skilled commuters in ten American cities found that dependence on public transit decreased employment access far more than any other factor analyzed, including residential location (Taylor & Paul, 1995). The cause, some suggest, is that jobs, especially of the low-wage service variety, are geographically inaccessible by public transit, a phenomenon often referred to as a *spatial mismatch* (Kain, 1968). Without transportation to dispersed job locations, inner city residents become trapped in poverty. With some exceptions, research supports the negative effects of the spatial mismatch hypothesis on the poor, but this does not explain everything (Ong, Houston, Horton, & Shaw, 2001).

There is growing attention to the effects caused by social determinants of place, including available transportation options, have on quality of life and the future prospects of the children who grow up there. Raj Chetty and Nathaniel Hendren's Equality of Opportunity Project (2015) found that the chances of a child growing up at the bottom of the national income distribution to ever one day reach the top actually varies greatly by geography. Segregation, family structure, income inequality, local school quality, and social capital are examples of factors that determine the overall quality of the environments under which children are raised. Chetty's work has, somewhat unintentionally, influenced transportation scholarship. One of the many variables in their model is a commute variable defined as the percent of workers whose commute time is less than 15 minutes each direction. It is not an indicator of overall average commute times of a community, though their findings are often misrepresented as such. Instead, it represents what happens when a larger fraction of a community have very short commutes. They find that is a much better predictor of children's upward mobility than many other measures of segregation. Though such an indicator would never have been used by traditional transportation planners, the finding has flagged commute time as an important factor in the debate over the best policy interventions to pursue.

With carlessness increasingly associated with poverty, many scholars have prescribed that policymakers focus on automobile ownership, rather than public transit, to alleviate poverty (Wachs, Samuels, & Skinner, 2000). It has been suggested that government relies on existing transit to provide service that is *good enough* thus perpetuating the disadvantage of those on welfare (Waller & Hughes, 1999). Over time, states have removed the treatment of automobile ownership in the asset limit determination for welfare and food stamps (Pirog, Gerrish, & Bullinger, 2017; J. Sullivan, 2006), as the capital value of their car comprises a significant share of the total wealth of poor families. Reliance on automobiles, particularly among poor single mothers, has increased since the 1990's (Blumenberg & Thomas, 2014). Low-income individuals are also considerably more likely to frequently transition into and out of car ownership status. Though the overall ownership rate of low-income households in the US has increased from 50% in 1960 to 80% in 2010, the cost of owning and operating an automobile has been increasing faster than inflation suggesting a disparate impact on low-income families (Berube, Deakin, & Raphael, 2008). While better automobile access is positively associated with future employment and greater income gains, the costs of owning and maintaining the vehicle outweigh the income gained from increased employment (Smart & Klein, 2015).

The problem with most of this research is that the predominant policy implication is that car ownership is the way out of poverty. While this is the case in sprawling automobile-centered metropolitan areas without good transit infrastructure, significant numbers of low-income urban resident relying on public transportation in locales where robust public transit systems exist. This suggests that different approaches should be taken to address urban mobility deficiencies for low-income individuals. While studies of Portland, Oregon and Atlanta, Georgia indicate that access to public transit is positively related to labor participation rates (Sanchez, 1999), only a weak association was found for the poor in Alameda County, California (Cervero, Sandoval, & Landis, 2002). Even if affordability is an issue, a study of welfare recipients indicated they preferred more frequent service rather than lower fares (Ong et al., 2001; Wachs & Taylor, 1998). Most studies on low-income and transit focus on travel-time disparities. The rational locator hypothesis suggests that individuals have a fixed travel time budget (choosing housing location accordingly), but some research indicates that this is not the case, instead showing that travel time is increasing over time and is a result of the spatial structure of metropolitan areas (Levinson & Wu, 2005). The distance and duration of commuting has increased the fastest for single mothers, and in addition, commute times using public transit have increased significantly compared with driving (Blumenberg & Thomas, 2014).

Clinton's 1996 Welfare Reform led to a brief period of renewed interest in the transportation needs of the poor. Because strict work requirements had to be met in order to receive welfare aid, transportation was identified as a significant obstacle to meeting these requirements. Responding to previous research on spatial mismatch, the U.S. Department of Transportation's Job Access and Reverse Commute and the U.S. Housing and Urban Development's Bridges to Work programs were introduced in 1998 to support the commutes of low-income transit riders to suburban job locations. These programs, though, rarely proved substantially beneficial (Cervero & Tsai, 2003; Goldenberg, Zhang, & Dickson, 1998; Turner & Rawlings, 2005). Scholars and practitioners acknowledge the important role mobility plays in the lives of low-income individuals, but little concrete progress has actually been made in addressing these concerns (Lucas, 2012; Sanchez & Brenman, 2010).

Commute time receives significant attention in scholarship and the press as a benchmark for how cities are faring with traffic congestion. Most notably, the Texas A&M Transportation Institute's annual "Urban Mobility Report" provides estimates of driving travel time delay for urban areas around the US (Schrank, Eisele, & Lomax, 2019). Data such as this, though, does not include transit nor provide disaggregated results by race or household income. Scholars have reported that low-income individuals suffer from longer commute times (Ong, 2002), but there are no rigorous studies to support this hypothesis. Scholars have long rallied around what is known as the Rational Locator Hypothesis which suggests that individuals maintain approximately steady journey-to-work travel times by adjusting their home and workplace (Levinson & Wu, 2005), and there is evidence that, on average, there is a universal desire for a 30 minute work commute each direction (one hour per day), referred to as the Marchetti's constant (Marchetti, 1994).

2.4 Affordability

The relative burden of transportation costs on a typical low-income household budget is about 30% (Table 2-1). Commonly, affordability is defined as households being able to spend less than 35% of their budgets on housing (rent/mortgage, property tax, insurance, utilities) and 20% of their budgets on transport, or less than 55% on transport and housing combined recognizing that trade-offs are made between these costs (Litman, 2014). A study of 25 low-income residents found that evading the fare, exploiting free transfers, forgoing goods, borrowing money, and using free fares provided by welfare providers were common compensating mechanisms (Perrotta, 2017). One study found that providing transit subsidies to clients of a non-profit employment agency increased job application and interview rates by 19% (Phillips, 2014).

Urban transportation subsidy programs are rare, which is somewhat curious given that the social safety net in the US includes support for housing, healthcare, and food, much of which requires transportation to access. With few exceptions, transit authorities do not provide discounts for low-income riders (Harmony, 2018). Since 1972, the federal government has mandated that 50% discounted fares for seniors and persons with disabilities are provided

Figure 2-1 Typical Household Budget in 28 Metropolitan Areas: Expenses as a Share of Income (Wachs, 2010)

	All Households (%)	Working Families with Incomes \$20,000–\$50,000 (%)
Housing	27.4	27.7
Transportation	20.2	29.6
Food	10.6	15.1
Health care	4.7	7.7

NOTE: Housing costs include mortgage payments, operating costs, and utilities for homeowners and contract rent and utilities for renters; transportation costs include the cost of owning and operating a vehicle and the cost of public transit.
SOURCE: Figures derived from the Center for Neighborhood Technology and the Center for Housing Policy from the 2000 Census of the U.S. Census Bureau and the 2002 and 2004 Consumer Expenditure Surveys of the Bureau of Labor Statistics.

as a stipulation for receiving federal funds, but there is no requirement for such a discount for those with limited means (McCollom & Pratt, 2004). As transit authorities across the United States raise fares to fund growing budget deficits and improved service, affordability has become a more dominant element in the public discourse of equity. The result has been a growing sentiment that means-based discounts be used as a potential public policy intervention to reduce poverty (Moffitt, 2018; Stolper & Rankin, 2016).

2.5 Elasticity

Transit pricing research received wide attention during the 1970s and early part of the 1980s by the U.S. Urban Mass Transportation Administration (UMTA) which actively sponsored a series of conferences, workshops, and research projects. In the wake of significant ridership decline and the shift from private to public ownership, policy makers were grappling with how much to fund public transit from user fees versus subsidies. In the mid 1980's, the neoliberal emphasis on privatization and competitive contracting drastically curtailed research on transit pricing. Since then, relatively little has been funded or published (Cervero, 1990).

There is a body of literature on fare elasticity with several meta-studies available (Holmgren, 2007; Wardman, 2014). Table 2-2 summarizes generally accepted transit fare elasticities. While these values are generally true in the one to two year short-run, they tend to approach one over the longer term. Fare elasticity is an important input parameter used by transportation modelers to estimate the potential impact of proposed interventions on the resulting behavior of individuals, specifically on an individual's choice of mode (or choosing to take the trip at all). These estimates are used in traditional four-step models (Bartholomew, 2006) to estimate, for example, the potential ridership of a proposed bus rapid transit line or to estimate ridership loss from a fare increase. A high value for elasticity indicates price-sensitivity whereby a relatively small change in price causes a relatively large change in consumption. Low elasticity means that prices have relatively little effect on consumption. Elasticity values less than one are referred to as inelastic (price changes result in less than proportional changes in consumption). Transit fares are generally considered inelastic by transit planners when the elasticity value is less than one.

Figure 2-2 Generally accepted transit fare elasticities (Litman, 2016)

Market Segment	*Short Term*	*Long Term*
Overall	−0.2 to −0.5	−0.6 to −0.9
Peak	−0.15 to −0.3	−0.4 to −0.6
Off-peak	−0.3 to −0.6	−0.8 to −1.0
Suburban commuters	−0.3 to −0.6	−0.8 to −1.0

The industry standard for fare elasticity is called the Simpson-Curtin rule: transit demand declines 0.33 for every one percent increase in the fare (Curtin, 1968). The Simpson-Curtin rule is based on a study of 77 cases of transit fare increases occurring over a twenty year period. The study correlated the percentage change in ridership for the three months following each fare increase with the percent change in the fare. Given the absence of any better information, this rule of thumb continues to be used. Typically, more essential trips, such as for work and during peak hours, are less sensitive to fare changes than discretionary ones. And studies show that price elasticities rise with income. From four case studies, the average elasticity for riders from families with annual incomes below \$33,000 was -0.19, compared to -0.28 for riders whose household incomes were above \$100,000 (both values in 2019 dollars).

Cost is not the only consideration for low-income riders. Some research has indicated that routing, frequency, schedule, and/or reliability constitute the most critical barrier, not necessarily cost: if transit worked for the needs of an individual, it would be worth the fares. Robert Cervero (1990) suggests that riders are approximately twice as sensitive to changes in travel time as they are to changes in fares, a compelling argument for operating more premium quality transit services at higher prices.

Difficulties disentangling the separate effects of car ownership and income on public transit use increases the challenge of understanding fare elasticities of the poor (Balcombe et al., 2004). Public transportation, when accompanied with sufficiently dense, mixed land uses, is considered a low cost alternative to driving. But when the inability to pay the fare is a barrier, equitable access across the economic spectrum is not achieved. There are two conflicting narratives regarding fare elasticity of low-income segments of the population. On the one hand, they are less likely to own or have access to a car, meaning that they are less able to avoid using public transportation in response to a fare increase. In marketing parlance, they are considered "captive" riders and would be expected to have inelastic response to fare changes even under conditions whereby the average individual might have an elastic response. Alternatively, lower-income riders might be less tolerant of the effects of a fare increase as it represents a greater proportion of their already constrained household budget. This would imply that their response would be more elastic than higher-income riders. A handbook from the United Kingdom states that those with higher incomes tend to have higher elasticity values because their higher car ownership levels mean that they have an alternative when fares increase (Paulley et al., 2006).

Fares are expected to have a varying impact on ridership based on income, yet few studies attempt to quantify the differential impact fares have on low-income riders. This is surprising given the importance many scholars place on public transportation as a critical factor in the lives of those on the low end of the economic spectrum. The latest Transportation Research Board handbook on the subject from 2004 indicates, "the effect of income on fare elasticities is not well researched" (McCollom & Pratt, 2004). One reason for such a lack of research is that fares are not found to be a major factor in determining aggregate ridership (Winston, 1985). The few rigorous studies of fare elasticity of low-income riders are contradictory in their findings. An often cited study of the 1966 fare increase in New York's subway system indicates that low income subway users were at least three times more responsive during all times of the day to fare changes than were average subway users (Lassow, 1968). However, ten years later, an analysis of the 1975 fare increase in New York City found the opposite result. Groups with annual household incomes of greater than $15,000 ($66,000 in 2015 dollars) were slightly more likely to change mode as a result of the fare increase than those earning less (Obanini, 1977). A study of the Chicago Transit Authority fare increase in the early 1980's found that lower-income riders (from households with incomes of less than $30,000 ($65,000 in 2015 dollars) had slightly more fare sensitivity for work trips than higher-income riders, but found no differential for non-work trips (Cummings & Fairhurst, 1989). Studies of several free off-peak transit experiments in the United States in the 1970's did not find a correlation between income and ridership response (Lago, Mayworm, & McEnroe, 1981).

A more recent study found mixed results when evaluating changes in ridership at individual Chicago Transit Authority rail stations following fare increases in 2004, 2006, 2009 and 2013 correlated to the per capita income in the neighborhood surrounding each station (Miller & Savage, 2016). One fare increase resulted in a greater decline in ridership in lower-income neighborhoods, but the reverse was found for another fare increase (no relationship between income and ridership response was found for the remaining two increases).

2.6 Accessibility

Access to opportunities, such as jobs, services, and social interactions, and are primary enabled by transportation services (Grengs, 2010). Policymakers are shifting away from using the number of transportation trips taken to evaluate policy interventions, and are instead utilizing accessibility as a more desirable metric (Stewart, 2017). The term *accessibility* in this context is not to be confused with evaluating the ability of persons with disabilities to maneuver through the built environment (e.g., transit vehicles, sidewalks, and building entrances), nor does accessibility refer to measuring the availability of a certain transport mode (e.g., access defined by living a certain distance from a transit stop or owning a vehicle.) Rather, accessibility refers to the ability to *access* desired goods and services. Demand for transportation is considered a derived demand because people travel in order to satisfy life's needs and desires. People ultimately engage in mobility to achieve access to various destinations. There are exceptions, of course; active transportation such as bicycling and walking serves also for exercise and enjoyment, and a certain amount of "downtime" during travel is considered valuable in and of itself (Páez & Whalen, 2010). While traditional mobility planning focuses on the trip itself, accessibility planning focuses on the end goal (Metz, 2008).

A commonly used metric for transit accessibility is the number of jobs reachable within a certain time frame (e.g., 45 minutes) by public transit. Here, commute time is used as an input variable as is done through accessibility analysis by transport geographers (van Wee, 2016). Scholars point to the problems with other metrics. Simply having a transit stop nearby ones home location does not necessarily equate to the ability to get to desired destinations: service might not be reliable, run at night, or permit the needed trip-chaining. A common problem with traditional mobility metrics is they evaluate social welfare by distilling all transportation characteristics, such as travel time and wait time, into monetary values. In doing so, assumptions about how individuals' value time bakes inherent inequity into the model (Lucas & Martens, 2019).

Quantification of accessibility requires the understanding of the purposes of transit trips taken, but there is limited existing literature on the relationship between transit use and trip purpose for low-income individuals. The focus on commute trips by traditional transportation planning professionals and academics marginalizes the importance of the many non-work needs of those with limited means. To understand issues of transit affordability, then, is to understand how cost constraints influence decisions about which destinations to access and which to skip. If residents are forgoing transit trips because of cost, it begs the question of what activities and services are being sacrificed. If activities and services are indeed being given up, it is important to understand why. If affordability is a factor, as is suggested by this research, it is also important to understand the decision making processes that lead to this outcome in order to best inform any policy interventions, such as a means-tested fare.

2.7 Critique

Sclar and Lönnroth (2016) assert: "few dispute the fact that the goal of expanding urban transport is to facilitate improved urban access" (p. 1). Transportation scholars and practitioners striving to improve such access in US cities have limited knowledge on which to recommend courses of action. Debates continue on whether to focus on public transit or vehicle access, and also whether cost is the predominant problem for low-income transit riders or inadequate service. A TransitCenter spokesperson claimed that, "the price of the fare matters to riders, but they prioritize frequency of service," and the Massachusetts Transportation Secretary Stephanie Pollack stated, "I'd like to provide a bus service that's good enough that people are willing to pay for it, rather than concede that service is terrible and we should offer it for free" (Vaccaro, 2020). The New York City advocacy campaign messaging for low-income fares relied heavily on the results of a phone survey conducted by the Community Service Society. When asked *which of the following do you think is the biggest problem with subways*, the highest response by low-income riders was *fares too expensive* (Stolper & Rankin, 2016). Policy makers and advocates in cities around the US have few rigorous studies to inform their decisions. This dissertation aims to fill this void by addressing the question of how low-income riders would change their behavior in response to discounted fares.

3

Research Design

This research takes a mixed-methods approach to better understand the travel behavior of low-income transit riders. Randomized controlled evaluation is the core method employed to determine the behavioral response to discounted fares. The experiment tests the effect of providing a 50% transit subsidy on a change in mobility and access to desired destinations for low-income transit riders in the core transit catchment area in the Boston region. Additionally, zero-inflated negative binomial regression econometric techniques are used to evaluate the influence of demographic and self-reported health covariates. Qualitative methods are used to better understand the underlying decision making mechanisms that drive the quantitative findings of the experiment. Semi-structured participant interviews along with direct observations of participant behavior though smart card data analysis are employed. This chapter details the research design including the rationale for the selected methods and case study site.

3.1 Randomized controlled evaluation

In a recent interview, the economist Esther Duflo said, "it's not the Middle Ages anymore. It's the 21st century. Randomized controlled trials have revolutionized medicine by allowing us to distinguish between drugs that work and drugs that don't work. And you can do the same randomized control trial for social policy. We feel very fortunate to see [evidence based policy] work being recognized." The interviewer added, "that's what the Duflo & Banerjee research is all about, trying to reduce the guesswork of economic development policy by seeing what seems to work, and what doesn't, at least in its current form."[1] Guido Imbens (2010) writes, "randomized experiments do occupy a special place in the hierarchy of evidence, namely at the very top" (p. 407). Conceptually identical to *randomized controlled trials*, commonly used in testing the effectiveness of pharmaceuticals, *randomized controlled evaluations* assess the effectiveness of public policy interventions.

The three key features of experimental study design are manipulation, control, and observation. In this context, manipulation means that the experimenter has the ability to introduce a shock into the existing order of things in the form of an intervention and is able to determine who does and does not receive it; this contrasts with econometric approaches using natural experiments where neither are the case. Control is most readily accomplished through random assignment. The procedures by which participants are assigned to either receive the treatment or not ensure that individuals have equal probability of assignment to either group. Random assignment ensures that individual characteristics or experiences that might confound the treatment results are, on average, evenly distributed between the two groups. By manipulating only one variable, the assumption is that the randomness of the

[1] From an interview on PBS News Hour Economics by correspondent Paul Solman with Esther Duflo and Abhijit Banerjee, November 21, 2019. https://www.pbs.org/newshour/show/how-these-2-economists-are-using-randomized-trials-to-solve-global-poverty

confounding factors is the same for each group and therefore cancels out when considering the difference in the mean values of the observable metric for each group. The third component, observation, requires that the researcher develop and be able to monitor a specific dependent outcome variable that accurately represents the construct of interest. Concerns arise if the measurement technique obtains the desired metric differently for each group.

There are several types of comparisons that could be made using randomized evaluation methodology (Murray, 1998). The hypothesis testing is set up based on the objective of the comparison. Most commonly used in the social sciences is *superiority evaluations* to verify that a new treatment is more effective than current conditions. There are two additional types of comparisons: *equivalence evaluations* try to show that the two treatments are equally effective, while *non-inferiority evaluations* try to show that the new treatment is at least as effective the existing one. For superiority evaluations, the hypotheses are set up as follows. μ_{treat} is the indicator for the treatment group, $\mu_{control}$ is the indicator for the control group, sd is the measure of the statistical accuracy of an estimate equal to the standard deviation of the theoretical distribution of a large population of such estimates. Z, the test statistic, obeys the standard normal distribution.

$$H_0: \mu_{treat} - \mu_{control} = 0 \qquad H_A: \mu_{treat} - \mu_{control} > 0 \qquad Z = \frac{|\mu_{treat} - \mu_{control}|}{sd} \tag{3.1}$$

3.1.1 History

While randomized controlled evaluations have been used for several hundred years primarily for medical research, they have only found their way into the social sciences more recently. In 1747 James Lind first used the concept of a control and experimental group in demonstrating the benefits of citrus fruits in preventing scurvy. Experimentation methodology first came to the social sciences in the early 1900's with agricultural field experiments by Ronald Fisher.

The publication of his book *The Design of Experiments* (1937) opened the social sciences to the use of randomization in controlled experiments. The field of psychology commonly employs the methodology which works especially well in highly controlled laboratory settings where the character of the intervention and the control groups are very clear. But randomized controlled evaluation did not enter mainstream social science until the 1970's with income tax experiments (Hausman & Wise, 1985). These were followed by labor market and welfare program evaluations which led to the passage of the Family Support Act of 1988, an overhaul to the Aid to Families with Dependent Children program (Manski & Garfinkel, 1992). The past 15 years has seen significant use of randomized experiments in the developing country health economics context, most prominently through MIT's Jameel Poverty Action Lab (J-PAL). More recently, a growing popularity of evidence-based policy making has also led to the broadening of randomized experiments in other social sciences and policy making arenas (Stoker & Evans, 2016).

3.1.2 Rationale

When evaluating methodological options for my research, I chose the randomized controlled evaluation approach because no other method could effectively quantify the behavioral impact of low-income fares. A stated preference survey is one alternative that can be used to evaluate expected responses to proposed fare changes, but these surveys are known for the lack of internal validity. An econometric approach requires a dataset that provides enough variation between the dependent variable (number of transit trips taken) and independent variable (transit cost). A cross-city comparative approach, while useful for helping to answer questions in the urban planning context, is a highly problematic approach in my case. There are too few US cities with robust transit systems to include in such an analysis and even incorporating a correction for cost of living leaves many exogenous factors. Cities where transit is the mode of last resort and is already priced low would generate results that are not generalizable to the types of cities currently considering low-income fare programs.

Another option is an interrupted time series analysis, or quasi-experimental time series analysis, which takes advantage of an external shock such as a fare increase. These *natural experiments* occur when a particular intervention has been implemented but the circumstances surrounding the implementation are not under the control of researchers (Craig et al., 2012). They are, though, more susceptible to bias than randomized experiments. Robust matching of the intervention and control groups at baseline can be challenging, but various analytical methods are available to assist, such as propensity scores, regression discontinuity designs, and difference-in-difference models, to help adjust for potential differences in the baseline characteristics of the two groups.

Natural experiments are commonly used to estimate the fare elasticity of demand by comparing ridership data before and after the increase, referred to as a *shrinkage analysis*. The many differences in the real world before and after the increase challenge the ability to draw conclusions regarding the effect of the fare increase itself. Fare increases affect the single-ride cost as well as pass prices, involve differential prices changes to cash and fare-media products, and are accompanied by concurrent service changes- all of which further confound the analysis. Econometric regression approaches can be employed to attempt to control for these factors to decrease the bias of fare elasticity estimates but require many assumptions regarding constructs that are challenging to observe and quantify. In some cases, variation based on who ended up receiving the treatment in a natural experimental setting is used to identify a causal effect. Without random assignment, the assumption that the two groups are exchangeable (on both known and unknown confounders) cannot be assumed to be true. For these reasons, natural experiments will never unequivocally determine causation. Nevertheless, they are frequently used to address research questions that cannot be approached in any other way. The few existing studies of fare sensitivity of low-income riders rely on such natural experiments of fare increases where ridership is measured before and after the increase. These studies provide contradictory results suggesting the limited explanatory power of the approach.

There are no existing quasi-experimental situations where a regression discontinuity design would be applicable. This technique requires provision of the treatment to have been contingent on some selection or eligibility criteria. For example, such an analysis could be conducted on senior discounted fares by comparing the travel behavior of those who are just under the 65 year old threshold traveling full fare and those just over 65 who are traveling with a discounted fare. It is not possible, though, to associate age data with ordinary smart card usage data for individuals just under 65 (age data is, though, available through the senior pass program.)

There are two other problems with using a quasi-experimental approach for answering my question. The first is that ridership today is most often measured using automatic fare collection data within which low-income individuals are not segmented. Therefore, elasticity calculations are predominantly conducted on aggregate. It is common to use Census-based demographic characteristics for the area surrounding transit stop locations as a proxy for income. There is a growing concern regarding the validity of this approach because of the necessary assumptions regarding the correlation between income and mode choice (Karner & Golub, 2015).[2] The second problem is relying on the assumption that fare elasticity is linear. This is problematic when attempting to use elasticity results from incremental fare increase quasi-experimental studies to estimate the impact of a 50% fare subsidy program.

Randomized control evaluation methodology is often considered to be the only means for obtaining reliable estimates of the true impact of an intervention. But there are many condi-

[2] US Census data does not provide cross tabulated data at the tract level for both income and commute to work mode choice.

tions under which such an approach is not ethical, politically feasible, affordable, logistically possible, or appropriate. There is also a tension between the quality of a study and the time it takes for results to become available. Often public policy processes have a limited window of opportunity (Kingdon, 1995). The use of research-derived evidence may be a key feature of most policy models but scientific evidence does not always carry the same weight in real-world policy-making settings as other types of evidence. Therefore, much to the chagrin of the research community, policymakers often move forward with the best available evidence as opposed to the most rigorous evidence possible. A study in the health sector found that 95% of policy makers reported that policy decisions were based on available evidence of similar policies implemented by other organizations regardless of the scientific merit or quality of the evidence (O'Donoughue-Jenkins, Kelly, Cherbuin, & Anstey, 2016).

For reasons cited in this section, alternate approaches would not provide the evidence that stakeholders in the Boston context desire and that I, as the researcher, believe would provide a meaningful contribution to the debate on low-income fare programs in the US.

3.1.3 Mathematical foundation

Scientists have long struggled with conducting social science experiments because of the fundamental problem of causal inference which states that it is impossible to compare the outcome in a real-world setting between an individual who does not receive the intervention and that same person had they received the intervention. Though the problem is *fundamental* without any solutions, there are workarounds. When studying physical science phenomenon in a laboratory setting, tightly controlled environments allow experiments to both test conditions with and without an intervention. A compelling argument is then made that the test without the intervention serves as a valid proxy for the unobservable event. This is much harder when working with people functioning in real-world settings. Proxies for the unobserved condition must be established differently. Social science researchers face significant challenges in isolating the cause of the effect of an intervention on only the intervention itself. For example, if observations are made both prior to and following the provision of an intervention, the *prior* condition serves as a counterfactual proxy. But there are many differences in both the individual and the real-world environment before and after the intervention that could have contributed to the difference in the observed outcome for that individual. The number of transit trips someone took before and after being provided a discount could be influenced by the person's job status, weather, or school vacation schedule. In essence, it is impossible to observe the counterfactual at exactly the same time and in the same environment for a given person.

Randomized controlled evaluation is a methodology used in the social sciences that overcomes this major deficiency. The problem of confounding factors is eliminated by designing an experiment where a population sample is randomly assigned to either a treatment or control group. If each group is considered identical at the outset of the experiment, and the indicator metric is averaged across each group, the assumption is that the intervention is the only factor that is the cause for a difference in the mean values for each group. This can be thought of mathematically by starting with Equation 3.2.:

$$Y_i = \beta_i T_i + \sum_{j=1}^{J} C_{ij} \tag{3.2}$$

where, Y_i is the dependent variable (e.g., number of transit trips taken) for individual i, T_i is a dichotomous treatment dummy variable with values 1 or 0 indicating whether or not i receives the treatment (e.g., a discounted transit card), and β_i is the treatment effect on individual i (indicating how much of an effect T_i has on Y_i), and the right-hand term represents the influence of all J covariates (the C_j's for individual i), observable or unobservable, on the outcome variable Y_i. This mathematical representation can be connected with the counterfactual approach, often referred to as the Rubin Causal Model (Angrist & Pischke, 2014). For each person i there are two possible outcomes of Y_i: Y_{i0} occurs if there is no treatment and Y_{i1} if the person does receive the treatment. In reality, we are only able to observe one as nobody can be both treated and untreated at the same time. Only one of the outcomes actually occurs, but not both. The other, then, would have been the counterfactual. But if we were theoretically able to observe both, we could calculate the difference between the two outcomes, $Y_{i1} - Y_{i0}$. The covariates would cancel out and we would be left with β_i representing the treatment effect. This individual treatment effect is in principle unobservable. People are neither homogeneous (no two people are alike) nor stable (no one person is in exactly the same state at two different points in time) such that it is impossible to carry out an experiment with two people or the same person twice.

The only possible workaround, then, is to estimate the causal effects on samples rather than individuals. Randomized controlled evaluation takes advantage of a simple mathematical concept that, on average, the mean of the covariate factors are assumed to be identical for each group and therefore cancel out when calculating the difference in the means of the dependent variable for each of the groups. The average treatment effect is the difference between the average outcome in the treatment group minus the average outcome in the control group so that, while we cannot observe the individual treatment effects, we can observe their mean. The average treatment effect is an estimate of the central tendency of the distribution of unobservable individual-level treatment effects. The difference in means is an unbiased estimator of the mean treatment effect. Very few assumptions are required. It does, though, rely on the fact that the mean is a linear operator such that the difference in means is the mean of differences. This does not apply to other statistics, such as medians, percentiles, or variances of treatment effects.

3.1.4 Criticism

Use of randomized controlled evaluation in the social sciences has been met with skepticism and criticism. Before offering a critique, Deaton & Cartwright (2016) summarize the perceived value of randomized controlled evaluations by saying, "they are taken to be largely exempt from the myriad econometric problems that characterize observational studies, to require minimal substantive assumptions, little or no prior information, and to be largely independent of 'expert' knowledge that is often regarded as manipulable, politically biased, or otherwise suspect" (p. 2). Criticisms of randomized controlled evaluation methodology do not attack the powerful mathematical logic and overall potential for finding an unbiased estimate of the causal effect of a deliberate intervention. But they do concern themselves with other aspects: (1) ideological, (2) ethical, and (3) methodological.

The primary ideological argument is that it can only focus on small micro-level issues and cannot address larger issues facing humanity. Randomized controlled evaluation requires the researcher be able to administer an intervention, control who gets it, and have a precise numerical metric to measure. A very limited number of applications meet these criteria. It also happens that interventions appropriately suited for this method are generally limited to tackling the symptoms rather than the underlying structural problems caused by larger socio-economic or political forces. The positivist approach insulates the researcher from investigating, and hence assigning responsibility for, the causes of the conditions under exploration. In sum, the overarching concern is that randomized controlled evaluation receives outsized attention considering it cannot be used to answer larger social questions.

Only providing treatment to one study group and not the other, can create ethical problems by creating short-term haves and have-nots. Even if presented in the context of providing a greater social good by participating in the experiment, there is an important element of fairness that researchers have a moral imperative to follow. Often, this is ameliorated by providing the treatment to the control group participants at the conclusion of the study.

The next group of concerns are methodological, primarily having to do with representativeness of the allegedly randomized cohorts, and the external validity of results when the intervention is scaled up in a policy. The smaller scope of the intervention may lead to undetectable effects of some covariates that will manifest during the scaling up of the program. Another is reliability. A single study establishes only one data point bounded on either side by a confidence interval such that the *true* effect size must be presented with statistical uncertainty. Even in the most carefully designed studies, there is the possibility that the single data point may be atypical. While randomized experiments minimize bias in outcomes from differences in unmeasured characteristics between treatment and control populations, complex interventions create other sources of estimation bias. A review of studies on welfare, job training, and employment interventions in the US found that retrospective indicators often produced results dramatically different from randomized evaluations and that the bias is often large (Glazerman, Levy, & Myers, 2003). Replication, therefore, should be required as it is for the natural sciences (Shadish, Cook, & Campbell, 2002). The health science field follows this expectation but critics argue that it is ignored by social science researchers. Donald Campbell (1969) laments that, "too many social scientists expect single experiments to settle issues once and for all. This may be a mistaken generalization from the history of great crucial experiments. In actuality the significant experiments in the physical sciences are replicated thousands of times" (p. 427).

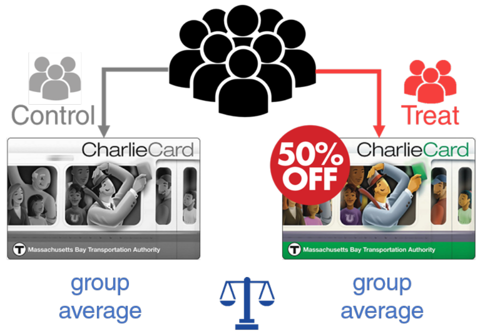
Other concerns regard external validity or generalizability. The experiment is carried out with a particular intervention, for a particular sample population, at a particular point in time, and in a particular geographic location. And many randomized controlled evaluations have high levels of specificity in each of those categories. While it may provide a valid estimate of the intervention's effect in the particular setting of the study, it is not necessarily generalizable to other situations.

3.1.5 Application

My research question regarding the impact of low-income fares on ridership is perfectly suited to be addressed using randomized controlled evaluation. While the question may be small, it has larger, immediate, policy-relevant implications. Though the method cleanly isolates the specific intervention of interest from the multitude of possible confounding variables, there were still obstacles to overcome, including: (1) developing instruments that can reliably measure outcomes; (2) conducting a study in a reasonable time frame; (3) managing the logistical and ethical obstacles in studying low-income populations; and (4) overcoming political obstacles in obtaining government cooperation to provide the elements required for me to study the phenomenon in a real-world setting.

Following is an overview of the implementation. 242 individuals from a low-income population sample were randomly provided either a smart card that provides a 50% discount (the treatment group) or an ordinary smart card (control group) (Figure 3-1). The study duration was two months. The core of the study was to quantitatively measure differences between the control and treatment groups for two concepts: mobility and accessibility. The concept of *mobility* was operationalized using the metric of number of transit trips taken as determined from analysis of smart card usage data obtained from the MBTA. To obtain trip purpose information, I developed a custom-built automated texting ChatBot tool to administer a daily travel diary by mobile phone text message. Here, the concept of *accessibility* was operationalized using trip purpose data reported in the travel diary. The treatment effect for each metric is defined as the difference between the average number of trips taken by the two groups.

Figure 3-1 Randomized controlled evaluation concept



The study was designed to mimic the policy intervention design and implementation that would be expected. Likely because of the existing 50% requirement for seniors and persons with disabilities, the current discussion around the US is provision of a similar 50% discount to low-income riders. Researchers often take an alternate approach. They measure aggregate transit use before and after a fare increase to determine the impact of the change and then use this elasticity to estimate the effect of half-price fares. Even if one believes the assumption that there are no other systematic differences in the world on either side of such a discontinuity, the relatively small increase in cost does not necessarily provide for an easily observable change in behavior and is not easily extrapolated to the behavior under a 50% discount scheme. In addition, it would not illuminate the sensitivity of low-income riders because it is usually impossible to segment smart card data by income.

What happens if a participant selected for the treatment chooses not to accept the treatment (but still agrees to be monitored)? Using the concept of *intention-to-treat*, the person should be kept with the treated sample during analysis to preserve the randomization benefit. This aligns with the real world in which we care about the final outcomes for the participants whether or not they receive the treatment. The uptake of the treatment certainly should be used as an indicator of its potential reach, but from an overall social welfare perspective, public policy only is concerned only with the aggregate outcome for everyone.

3.2 Case site selection: Boston

3.2.1 Rationale

There were several considerations that led me to select Boston as the case site for my research. Following the many scoping conversations with government, advocates, and other researchers, I decided on a study designed utilizing a randomized controlled evaluation methodology. I wanted the study design to reflect real-world conditions as much as possible. While I could have executed a study using ordinary smart cards and then reimbursed the treatment group participants for 50% of their costs at the conclusion of the study, this would have introduced bias as low-income behavior is more influenced by immediate costs as opposed to the potential for future returns than those who are better off financially. Close collaboration with a transit agency would be needed to obtain discount smart card media necessary to conduct the study under conditions more closely reflecting how a means-tested smart card would work in reality. Leveraging my existing relationship with MBTA staff, they were willing to collaborate. In addition, MIT has an existing research relationship with the MBTA such that I could easily access smart card data for analysis. Finally, the Fiscal Management and Control Board (the oversight body of the MBTA) was particularly interested in obtaining evidence-based research on low-income fares to clarify the question of whether the cost of the fare was indeed a barrier for low-income individuals and a means-tested fare would provide tangible benefits before pushing further for such a policy interventions.

Boston is a good case study location for other reasons as well. It is a city that has robust public transit such that car ownership is not required. With most affordability studies and policies in the US attending to car ownership as a necessary transportation intervention to escape poverty, Boston allows for the study of transit affordability as a potential barrier.

Figure 3-2 Boston Globe article, January 8, 2016 (Dungca, 2016)

Boston is well known for high levels of racial segregation and inequality (Holmes & Berube, 2016) suggesting it is a worthwhile place to study from an equity and justice perspective. US Representative Ayanna Pressley recently said:

> Although the 7th [district] is one of the most diverse, vibrant and dynamic districts in the country, we also are one of the most unequal. From Cambridge to Roxbury, life expectancy drops by 30 years and median household income by almost $50,000. Now what is happening here in the Massachusetts 7th, and the burden disproportionately bore by Black Americans is not an anomaly which speaks to the historical and systemically embedded challenges for black Americans. Black home ownership is only 30% while overall in our region it is 64%. We cannot end systemic injustices if those closest to the pain aren't closest to the power driving and informing our policy making.[3]

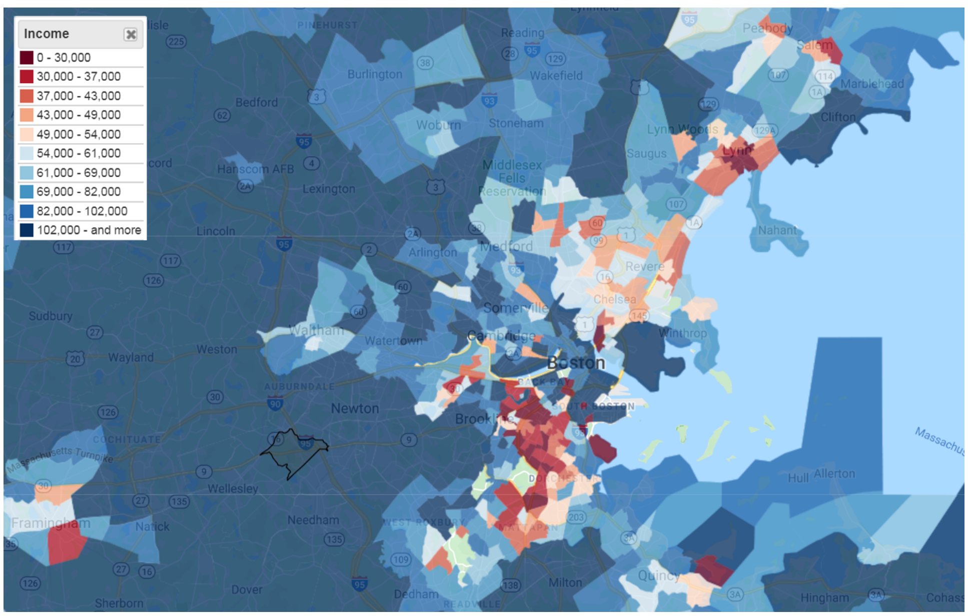
As the maps in Figures 3-3 and 3-4 illustrate, there is a high concentration of low-income and non-white population in the lower part of Boston, a result of racial segregation policies known as *redlining*[4] that began in the 1930's following the Great Depression (Jackson, 1985).

[3] Transcribed from the Congressional Black Caucus press conference held at Northeastern University, January 10, 2020 https://www.facebook.com/RepAyannaPressley/videos/2403261736452423/.

[4] The Home Owners' Loan Corporation, a subsidiary of the Federal Home Loan Bank system, created maps that color-coded neighborhoods and entire cities based on assessed risk using red to designate

Home ownership loans were not made available to these predominantly minority communities which were officially designated too risky, thus denying residents and their landlords the capital needed to maintain and modernize buildings, leaving many to fall into disrepair. These patterns linger today (**Coates2014TheReparations**; Massey & Denton, 1993). The median wealth of Boston's white households at $250,000 and that of African American households at just $8 (Muñoz et al., 2015).

Figure 3-3 Economic segregation (darker shading indicates census tracts with lower average median houshold income)



Source: http://www.justicemap.org

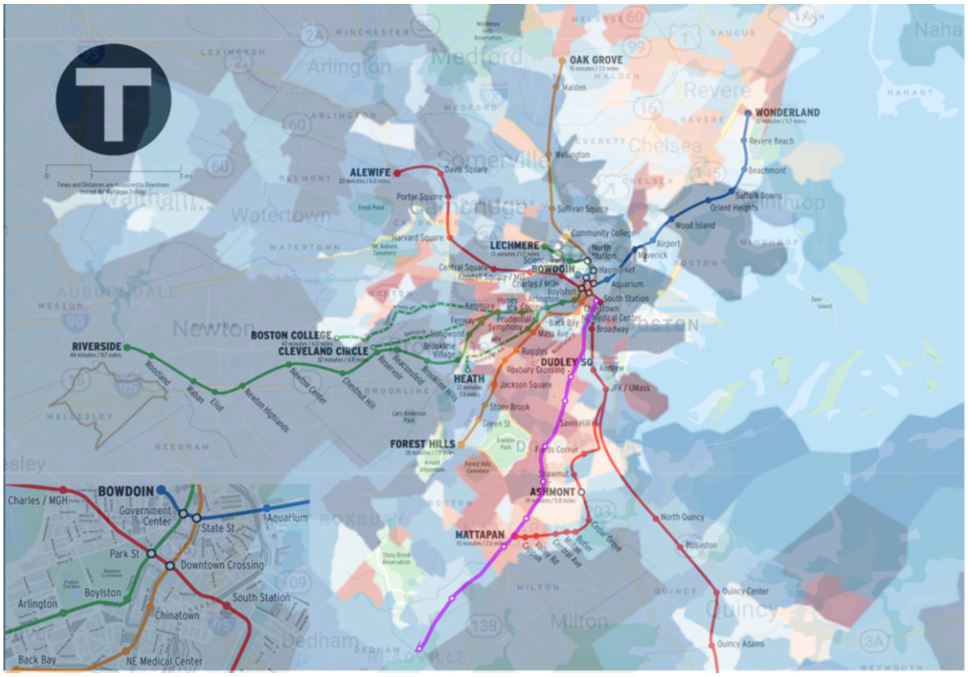
the most risky neighborhoods, predominantly those with a high percentage of residents of color, giving rise to the term *redlining*.

Figure 3-4 Non-white segregation (darker shading indicates census tracts with higher non-white residents)

Source: http://www.justicemap.org

The map shown in Figure 3-5 shows the orange and red rapid transit lines flanking either side of the lower income neighborhoods of Roxbury, Dorchester, and Mattapan. There has been a long push for the the commuter rail line shown in purple, known as the Fairmount Line, to provide more frequent service to bring it more on par with rapid transit (Jeremy Levine, 2013).

Figure 3-5 Subway (red, orange, green, blue), and Fairmount Line commuter Rail (purple) overlaid on average median household income (darker shares indicates lower values)

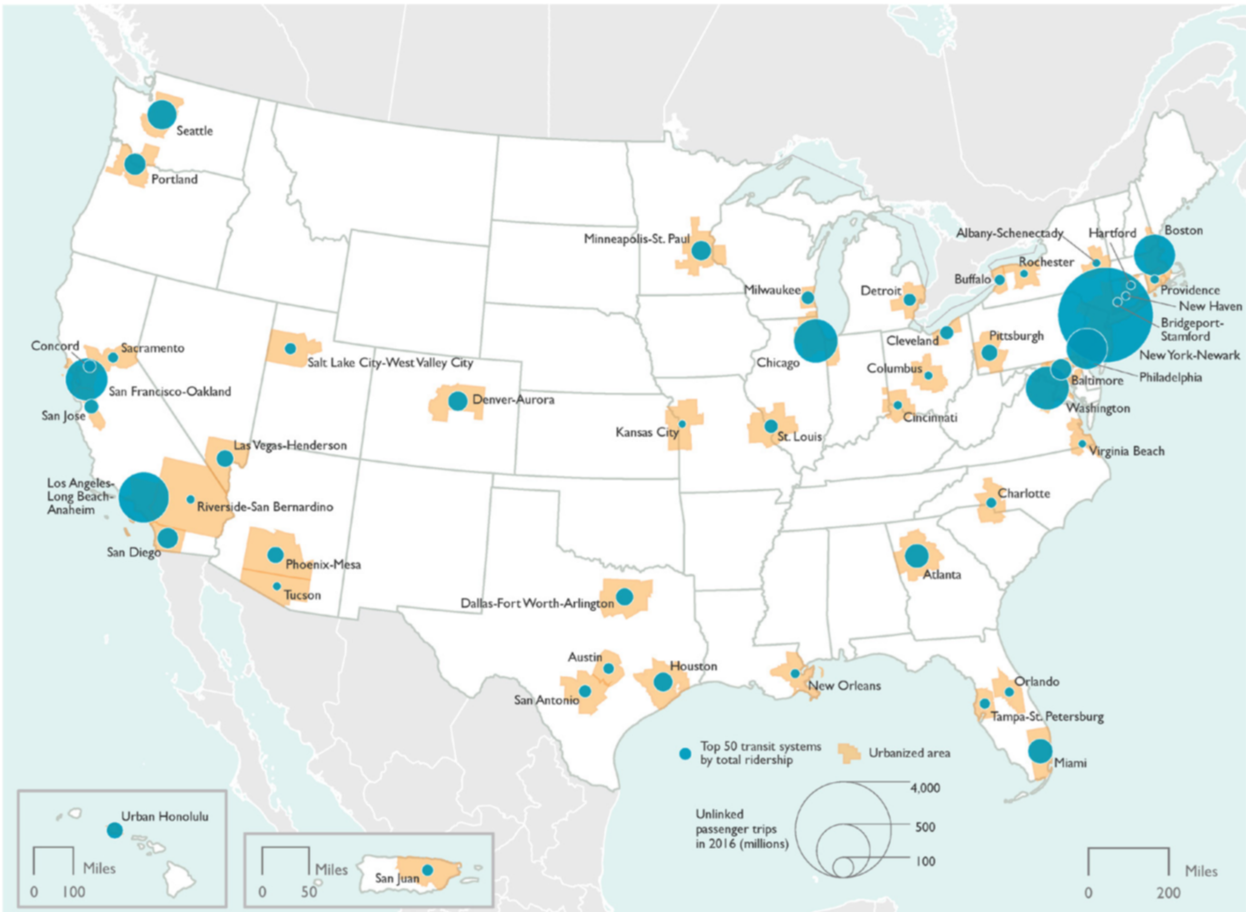


3.2.2 Context

Boston's MBTA system is the fourth largest transit agency in the US measured by passenger trips. Boston's approximately 400 million annual passenger trips is on the same order of magnitude as Chicago, Los Angeles, Washington DC, and Philadelphia. Figure 3-6 highlights the urban areas in the US with greatest transit ridership.

The MBTA operates rapid transit, bus, commuter rail, ferry, and paratransit services, providing about 1.2 million passenger trips per day (Figure 3-7). Rapid transit accounts for over half of all trips and buses about a third. A significantly higher percentage of low-income and minority passengers rely on the bus network (42%) than the subway (26%). And while only 7% of low-income passengers use the commuter rail, there is growing attention to its high fares and the implications for those being displaced from the urban core to nearby communities and gateway cities served by commuter rail (Haney, Corley, & Forman, 2019).

Figure 3-6 Top 50 transit systems by total ridership in 2016 (Bureau of Transportation Statistics, 2018)



The bus and rapid transit networks are shown spatially in Figures 3-8 and 3-9. Of particular interest is how poorly rapid transit serves low-income communities who rely primarily on the bus network alone or use the bus network to access rapid transit. Additional maps are provided in Appendix A.

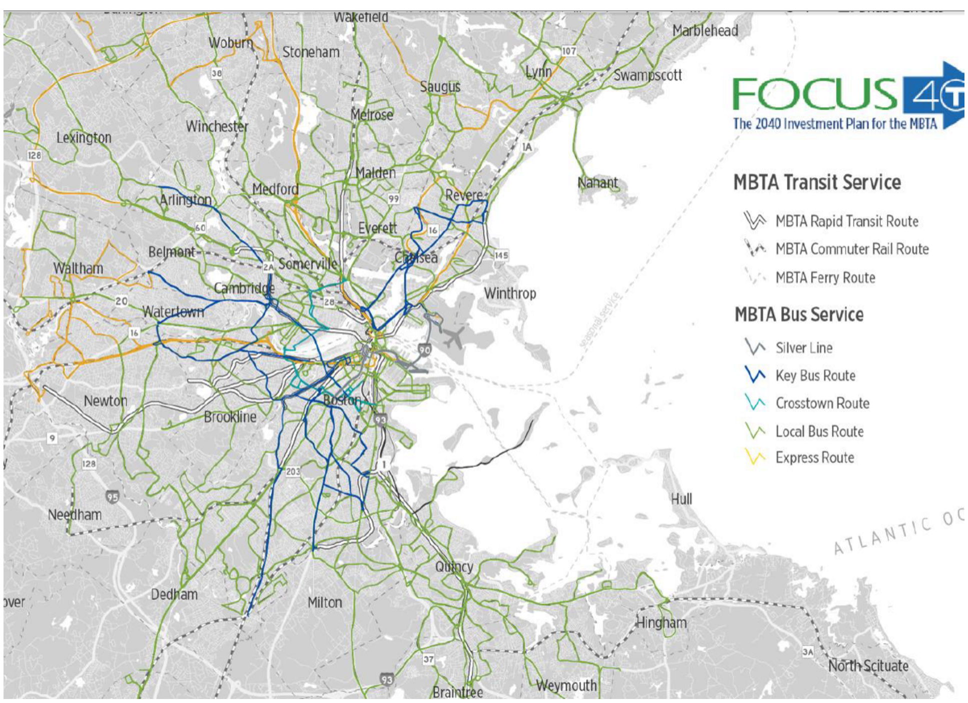
Figure 3-7 Ridership and income distribution by mode

	Daily trips		% low-income†	% minority
Paratransit (the RIDE)	6,000	0.5%	84%	23%
Bus	400,000	32%	42%	48%
Subway	700,000	57%	26%	31%
Commuter Rail	120,000	10%	7%	15%
Ferry	6,000	0.5%	4%	2%
	1,200,000	100%		

† %Low-income defined as household income under 60% average median income (AMI)

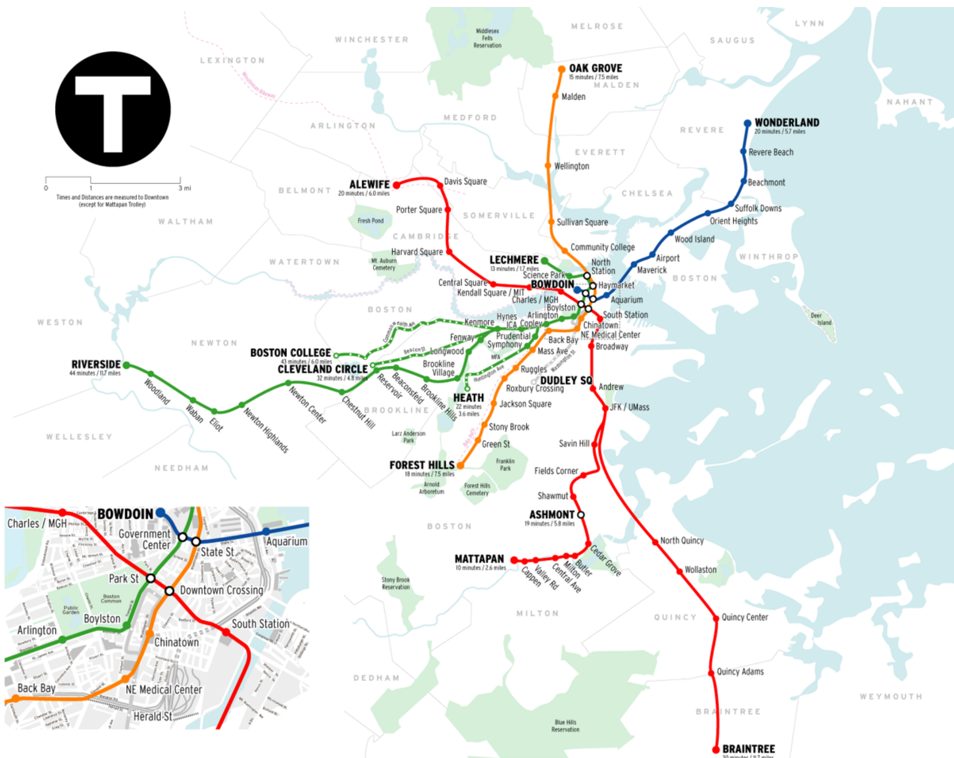
Source: MBTA 2015-2017 passenger survey https://www.ctps.org/apps/mbtasurvey2018/ and MBTA Data Dashboard, 2019 https://mbtabackontrack.com

Figure 3-8 MBTA bus map



Source: https://www.mbtafocus40.com/mbta-today

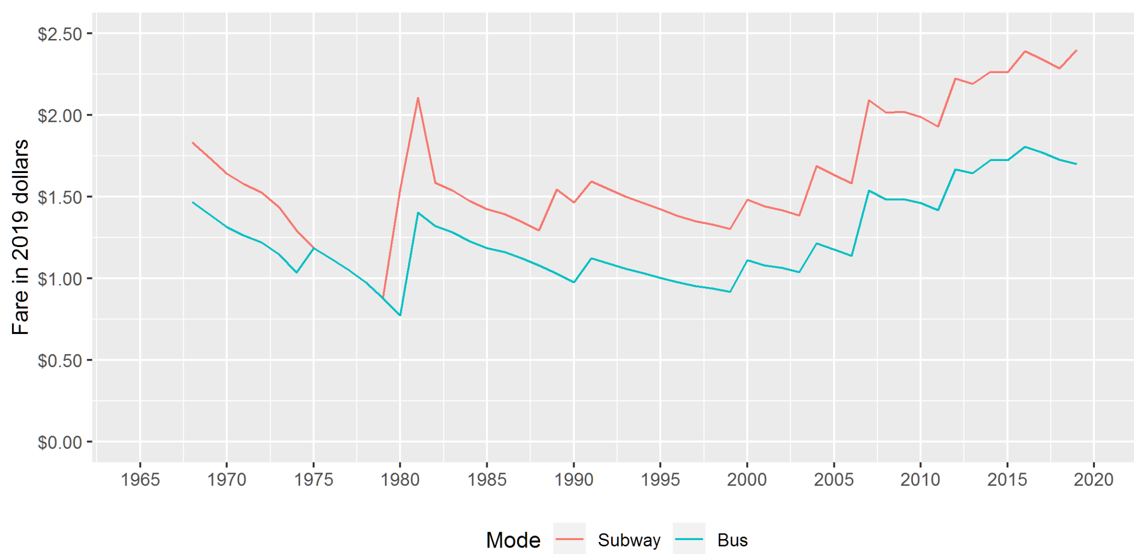
Figure 3-9 MBTA rapid transit map



Source: https://commons.wikimedia.org/wiki/File:MBTA_Boston_subway_map.png

A historic look at subway and bus fares over time (presented in constant 2019 dollars) is shown in Figure 3-10. Minimal fare changes in the 1970's led to a sharp increase in transit pricing in the early 1980's. Within a year, rapid transit fares were reduced as a result of a more than 10% decline in ridership.[5] After another period of slight decline in value of the fare, regular increases starting in the 2000's have brought the fare to levels exceeding those in the 1960's (in 2019 dollars). In constant dollars, fares have almost doubled over the past two decades.

Figure 3-10 MBTA fare history (in constant 2019 dollars)



Source: https://en.wikipedia.org/wiki/Massachusetts_Bay_Transportation_Authority#Subway_and_bus_fare_history

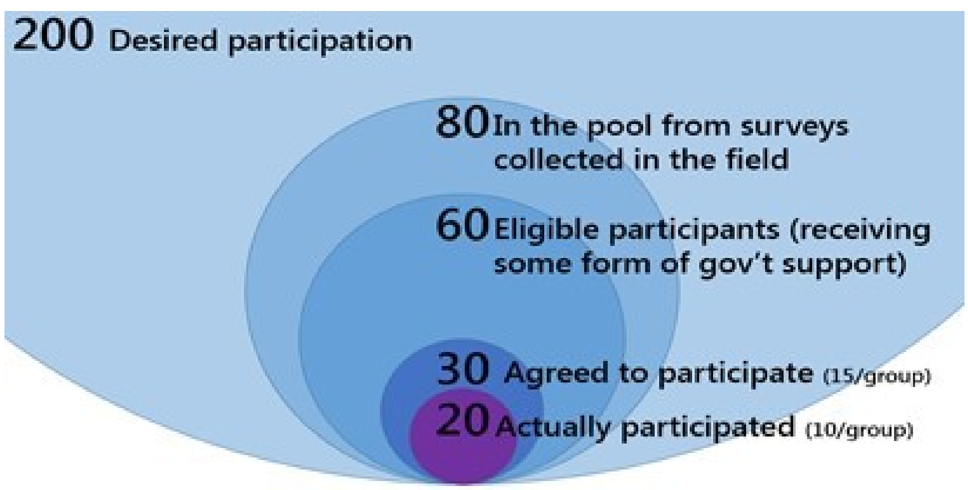
3.2.3 2017 Pilot

In spring 2017, I piloted a study on a small scale. I garnered a team of volunteers to recruit participants at Nubian Station (formerly Dudley Station) in the Roxbury neighborhood of Boston, one of the busiest bus stations serving a high proportion of low-income riders. To

5 Boston Globe, February 3 and 4, 1982

increase the level of trust that it was not a commercial sales effort, I provided name tags identifying the volunteers as being affiliated with MIT. Tablets running survey software were used for the recruitment allowing the participants the option to answer the eligibility questions themselves without the volunteer seeing. A total of 80 person-hours spent in the field over the course of two weeks yielded a mere 80 potential participants of which only 40 were actually eligible (Figure 3-11). The methodology for the pilot was to randomize the participants into the control and treatment groups and study behavior for one month. Because recruitment was easier if promising a discounted card for a month, the control group was given a discount card for the second month. MIT's institutional research board (IRB) required written consent from each participant which required the participant to return the form by mail in a self-addressed stamped envelope, a process which also significantly reduced participation. In the end, only 20 participants were in the study meaning 10 per study arm.

Figure 3-11 2017 pilot study recruitment

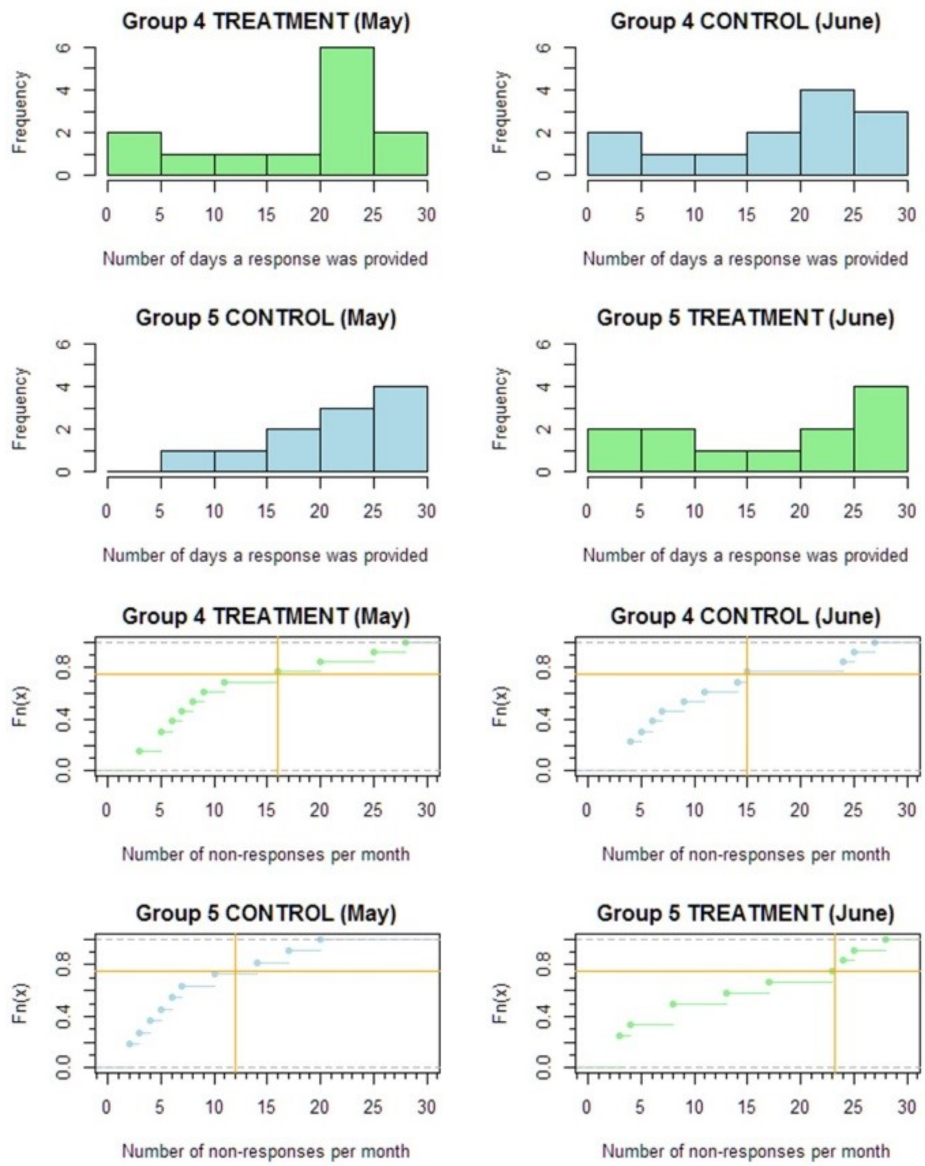


There were several key takeaway lessons learned from conducting the pilot. The first is that a better mechanism for recruitment was needed in order to have a larger, more representative, and random sample. Hence, the need for collaboration with the state's food stamps office for outreach. Second, the need to automate the intake process especially the

Institutional Research Board consent requirement. Luckily, the request to allow consent by text message was granted for the main study.

The most important finding from the pilot was the surprisingly high response rate to the ChatBot daily diary. Looking at Figure 3-12, the plots on the right present these results as a cumulative distribution. The percent of participants who did not respond to x number of texts or fewer is shown. The orange line indicates the third quartile (75%) mark. For example, for group 4, 75% of participants responded to 15 or more ChatBot texts over the course of the month for both treatment and control groups. On the other hand, 75% of Group 5 responded to 18 or more texts during the control month and only seven or more during the treatment month. It is difficult to explain the differences in response rate, except as a result of the small sample size not capturing the wide variance of participant behavior. Nonetheless, the response rate was much higher overall than expected. I believe this was, to a large degree, related to the $5 daily lottery incentive.

Figure 3-12 2017 Pilot ChatBot Response Rate

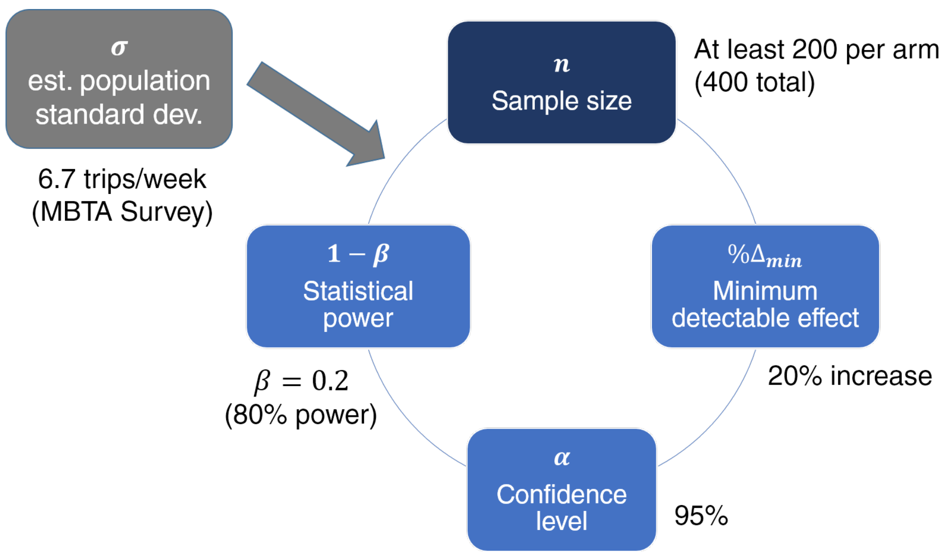


3.2.4 Sample size calculations

For the full study, I needed to estimate the necessary sample size based on the expected effect size I wanted to be able to detect. The desired sample size n is a function of a variety of factors (Equation 3.3 and Figure 3-13). α is the acceptable Type I error, β is the acceptable Type II error, $\%\Delta_{min}$ is the minimum relevant percent difference that would suggest the treatment had a relevant effect. The estimated population standard deviation σ_{pop} is a relevant factor as a larger value suggests we would expect more variation in our sample, thus requiring a larger sample size. Determining an adequate sample size, then, requires balancing these tradeoffs.

$$n = f(\alpha, \beta, \%\Delta_{min}, \sigma_{pop}) \tag{3.3}$$

Figure 3-13 Tradeoffs in determine the necessary sample size for randomized controlled evaluations.



First, the acceptable error rates are established. Applying probability theory, we are never able to claim anything definitively from the results, only the level of confidence we have that we did not see the results out of chance. In statistical hypothesis testing, Type I error occurs when one incorrectly rejects the null hypothesis when it is in fact true (also called a *false positive*). The probability of committing a type I error is most commonly set to $\alpha = 0.05$ meaning it is acceptable to draw a conclusion if I believe there is less than a 5% chance that the result was not witnessed by chance.

A Type II error occurs when one fails to reject the null hypothesis when in fact it is false (or *false negative*.) In such a case, researchers conclude that there is no difference between two groups when in reality a difference exists; there is no evidence that the compared samples come from different source populations. It is this Type II error rate that represents the power of the research study. Conventionally, the power $(1-\beta)$ is set at 0.80 which is equivalent to $\beta = 0.2$, meaning that the researcher wants less than a 20% chance of a false negative conclusion (an 80% probability of avoiding a false negative conclusion.

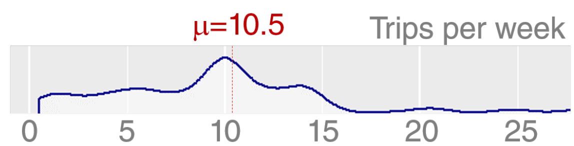
The next step is to determine the minimum detectable effect (MDE) of interest, which is the minimum difference between the studied groups that the researcher wishes to detect. In the social sciences, this value is determined by a difference that would make for compelling policy-making making. For continuous outcome variables, the minimum relevant difference is a numerical difference. In the case of the impact of low-income fares, seeing at least a certain percent increase in the number of trips is an appropriate construct for making a public policy decision. One could imagine stating in a conversation with an elected official, "low-income fares provide for at least a 10% increase in the number of trips taken." For comparison, the Youth Pass subsidy study conducted by the MBTA showed a 12% increase in the number of trips taken for individuals enrolled in school, and a 67% increase for those not enrolled in school (Paget-Seekins, Demchur, Reker, & Scott, 2015). For planning purposes, the challenge is the trade-off between $\%\Delta_{min}$ and power. As discussed below, using a $\%\Delta_{min} = 10\%$ and $power = 80\%$ leads to an overly ambitious sample size, so settling for a $\%\Delta_{min} = 20\%$ detectable effect size is more reasonable.

The significant challenge in determining an appropriate sample size is the need to know in advance the underlying average and standard deviation of the distribution of the indicator being studied. This is often not known very accurately prior to conducting the study. Data for the number of trips taken by low-income populations in the MBTA system are not available. Data are available for the ridership as a whole, but the literature suggests that the travel behavior of low-income riders would be different from that of the average population. The limited data that is available comes from a 2008 MBTA ridership survey. Low-income respondents took on average more weekly transit trips than non-low-income riders, and the sample had a much higher standard deviation (Figure 3-14).

Figure 3-14 Distribution of the number of weekly MBTA trips by income status (2008-9 MBTA Systemwide Passenger Survey)

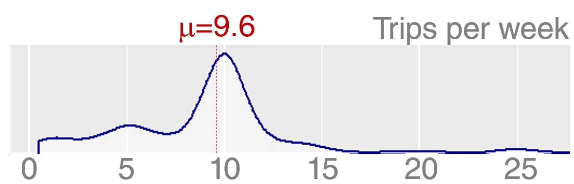
Low-income

	μ	σ
Bus	10.1	6.7
Subway	10.8	6.7



Not low-income

	μ	σ
Bus	9.2	4.9
Subway	9.9	4.8

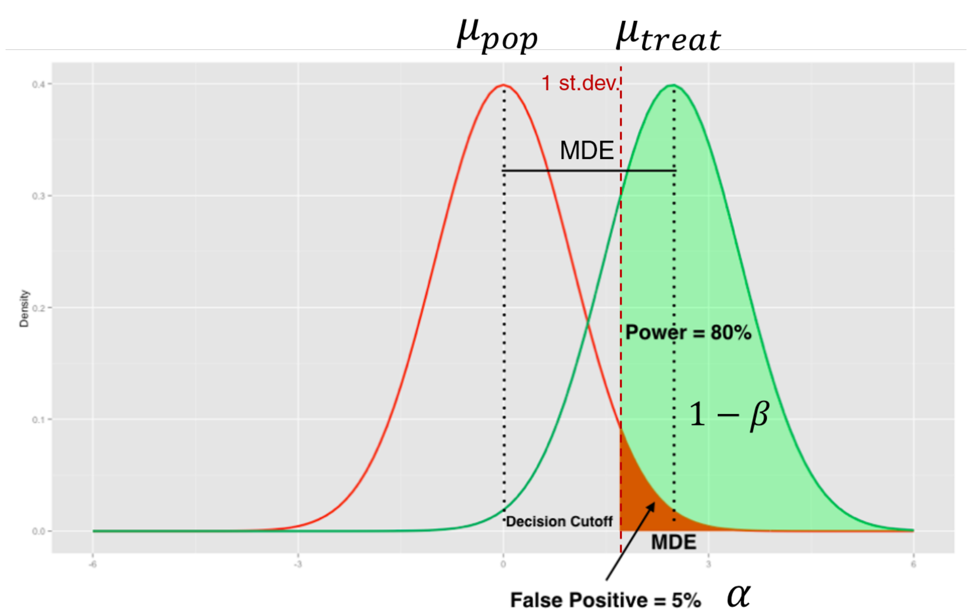


From the data above, the following parameters were determined by simply averaging the values from the bus and subway together. Clearly the large standard error associated with low-income population will require a larger sample size or reduce the power of the study. The minimum detectable effect size, based on the current value for the existing population, is calculated using $\Delta_{min} = \mu_{pop} \times \%\Delta_{min}$. The minimum detectable effect desired is 1 trip per week.

$$\mu_{pop} = 10.5 \frac{trips}{week}$$
$$\sigma_{pop} = 6.7 \frac{trips}{week}$$
$$\text{MDE} = \mu_{pop} \times \%\Delta_{min} = 10.5 \times 0.10 \approx 1 \frac{trip}{week}$$

The smaller the minimum relevant difference desired between the assumed population mean μ_{pop} (which would be the observed average of the control group $\overline{x}_{pop}$ in the study) and the assumed treatment mean μ_{treat} (which would be the observed average of the treatment group $\overline{x}_{treat}$ in the study), the smaller the power. Figure 3-15 helps illustrate this in relation to power. As the treatment curve (on the right) is shifted to the to the left (reducing the minimum detectable difference), the statistical power (green area) bounded by both the curve and also the one standard deviation line from the control group grows smaller.

Figure 3-15 Conceptual illustration of statistical power

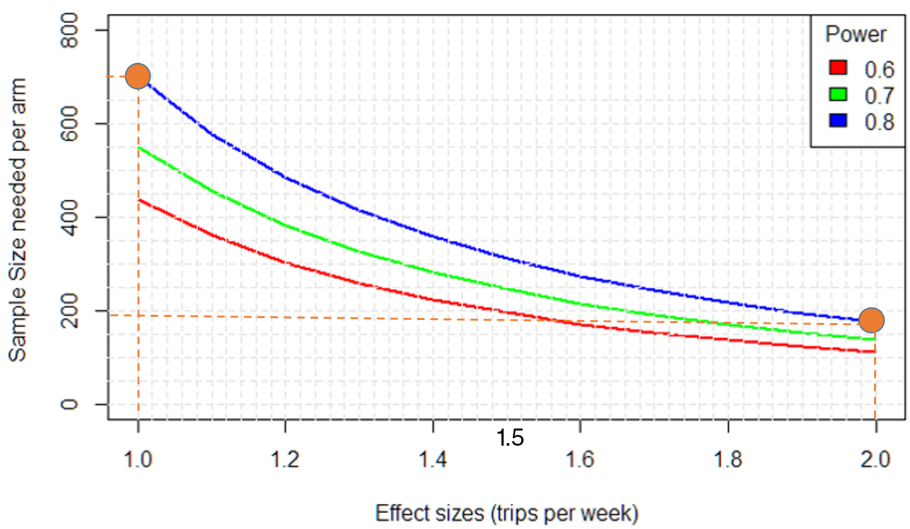


The required sample size is calculated using the above parameters. For a superiority design with two samples and a continuous outcomes variable, the sample size formula is shown below.

$$n = 2 \times \left(\frac{x_{1-\frac{\alpha}{2}} + z_{1-\beta}}{\frac{\text{MDE}}{\sigma}} \right)^2 \qquad \frac{\text{MDE}}{\sigma} = \text{the normalized minimum detectable effect size}$$

The calculations were performed using the `pwr` package in the statistical software `R` which implements power calculations as defined by Cohen (1988). The tradeoffs in terms of required sample size as a function of minimum effect size and power is shown in Figure 3-16. In order to detect a 10% change in the number of trips (+1 trip per week) with 80% power, 700 participants per arm are needed, outside the scope of possibility. Settling for a MDE of 20%, or +2 trips per week, brings the required sample size down to a more manageable 200 per arm.

Figure 3-16 Sample size estimation results: the required sample size per arm as a function of the minimum detectable effect is shown along with curves for different power values.



3.2.5 Engaging with marginalized populations

Researchers commonly indicate concerns with recruitment and sustained engagement of low-income populations for studies. These hard to reach, or *hidden*, populations are often difficult for researchers to access cost-efficiently in large numbers for successful statistically based study designs. There does not seem to be consensus in the research community regarding best approaches and methods. In reviewing the literature on the topic, much emanating from the health field, a variety of findings and suggestions are relevant and were incorporated into my research design. Overall, researchers recommend planning for extended time frame, higher resourcing costs, and collaborative community partnerships.

Bonevski et al. (2014) conducted a systematic review of strategies for improving health and medical research with socially disadvantaged groups. On a sociopolitical level, many studies reported potential participants, particularly African Americans, are skeptical of researchers, who are more often white. Another was a perception that the research provided no personal benefit to the participant or their community and, in some cases, may actually cause potential harm or stigma. Researcher exploitation of communities without regard for the value of their time or limited resources was also noted. Power-difference dynamics, reflecting unequal authority, often increased mistrust (Dancy, Wilbur, Talashek, Bonner, & Barnes-Boyd, 2004). For randomized controlled evaluations, some community partners expressed concerns that some participants would not receive the (likely beneficial) intervention. On a more nuts-and-bolts level, low literacy and language barriers were cited as issues requiring particular attention. A common barrier to follow-up data collection was maintaining participant contact because of the transient nature of those in many socioeconomically disadvantaged groups, such that phone numbers and addresses change frequently. This is especially important for longitudinal studies.

The most commonly used strategy for maintaining involvement of participants throughout a research project was the use of incentives and gifts. Cash incentives were reported to be more effective than non-cash incentives except for one study that found that financial cash incentives were disliked by young Latino women who instead preferred grocery or department store gift-cards. The use of branding or logos on non-cash gifts was reportedly effective. Utilizing a toll-free number to enable easy access to the researchers was cited as a successful strategy to improve connection with the participants.

One study attributed retention success to a coordinated effort between the research team and the staff at the clinical sites, project branding and a dedicated phone line (Nicholson et al., 2011). While most studies consider financial compensation as a core motivational element for participation, some studies indicate that financial compensation was least often cited as important (Gross, Julion, & Fogg, 2004).

Partner-led recruitment collaborations, in which community partners develop and manage the recruitment efforts at their sites, are commonly cited as being the most successful approaches. One study found that this method led to an enrollment rate of 68%, a far higher rate than achieved through other outreach approaches such as recruiting at large public events such as farmers markets, organizing special local recruitment events or recruiting at local organizations. It was also the most efficient with 34% of those approached through partners ultimately enrolled versus the $0\% - 17\%$ enrolled through other strategies (Horowitz, Brenner, Lachapelle, Amara, & Arniella, 2009).

Direct mail and social networking received attention as potential recruitment mechanisms. Several studies suggest that understanding how the brain processes information can help us to better understand why certain outreach techniques might be more successful than others. A study by Canada Post in collaboration with a neuromarketing research and strategy firm found that direct mail led to taking action more often than digital media because its physical format stimulates the underlying mental processes that guide consumer behavior.[6] Another study by the United States Postal Service found that Millennials respond positively to the low-tech marketing approach of direct mail. 84% of Millennials take the time to look through their mail and 64% indicated they would prefer to scan for useful information in the mail rather than email. In the study, neuroscience researchers found benefits in printed media: content was internalized more quickly, triggered activity in a part of the brain that

[6] https://www.canadapost.ca/assets/pdf/blogs/CPC_Neuroscience_EN_150717.pdf

corresponds with value and desirability, elicited a stronger emotional response, and was remembered longer.[7] The *Direct Marketing Association* found that direct mail receives a response rate of 4.4% (though declining) while email only 0.12%.[8] The latter study concluded with several useful direct mail suggestions: be creative, elicit an emotional response, and offer a clear call to action.

I incorporated several elements of these findings into my research design and highlight them below.

- *Trust.* I included endorsements from the Mel King Institute for Community Building[9] and the T-Riders Union[10] on outreach materials.
- *Branding.* I developed a logo to be used on all materials to create a stronger sense of association.
- *Research access.* I created a dedicated google account with a googlevoice phone number that could be used for calls and text messages.
- *Care.* I ensured that I responded quickly and with compassion and understanding to participants.
- *Maintaining contact.* I provided a refrigerator magnet to help keep my phone number available in case their smart card or phone was misplaced or lost.

3.2.6 Participant recruitment

There are several ways to develop a pool of study participants. One is manual recruitment, such as at a busy transit station, but that is incredibly labor intensive. This was attempted for the 2017 pilot study with poor results in part because of the challenge in targeting the specific population of interest (those with limited economic means) in a public setting. A

[7] https://www.uspsdelivers.com/still-relevant-a-look-at-how-millennials-respond-to-direct-mail/
[8] https://www.dmnews.com/marketing-channels/direct-mail/news/13059655/dma-direct-mail-response-rates-beat-digital
[9] https://melkinginstitute.org/about-us
[10] https://ace-ej.org/tru

second method is direct-mail outreach using a purchased mailing list of low-income individuals. Research into this idea revealed that such mailing lists are expensive and of low quality especially because of the lower rate of credit information and the more transient population. Another is partnering with an existing smaller non-profit organizations that work directly with low-income populations. While there is the advantage of easier recruitment, there is a significant disadvantage of generating a non-representative sample because clients tend to self-select to be part of these organizations. Finally, there is partnering with a large government agency which is what I decided to do.

A common concern is that the recruitment process will yield control and treatment groups that are no longer equivalent. This most commonly happens when people decline participation when they find out they are assigned to the control group and will not receive the treatment. To ameliorate this problem, I utilized a recruitment process that only told people that the study is about gathering trip purpose and enticed participation because of the daily lottery. People who choose not to participate will have done so with equal randomness. This provides for an adequate allocation concealment mechanism (ensuring the allocation is unknown and not predictable by the participants until the randomization has been completed.) While this method increases the integrity of the study, the downside is not being able to use the 50% discount card as a recruitment tool.

An alternate option often used in randomized evaluation studies is to eventually give everyone the opportunity to get the treatment. This is primarily done as an ethical consideration. The concern, though, is that there might be a non-negligible effect on the participant in anticipation of receiving the benefit. For the case of the 2017 pilot study, all participants were told they would get the discount card either in month 1 or month 2 when recruiting. Month 1 was considered the randomized evaluation study, and month 2 was extra, necessitated by the outreach methodology which promised a discount card.

The selection criteria for individuals was set as follows: (a) from a low-income population means tested by another agency, (b) not currently eligible for a discount transit card, (c) living in close proximity to transit such that it is reasonable to expect that transit could be part of their regular transportation. The sampling mechanism should provide for as random a sample as possible.

The most desirable participant sample is one representative of the target population appropriate for the policy being studied. While the MBTA could take responsibility for conducting the means-testing and therefore have flexibility on the eligibility requirements, other transit agencies, such as King County Metro in Seattle and the MTA in New York City, chose to collaborate with one or more social service agencies to determine eligibility. This is one of the main concerns of transit agencies as they struggle with managing their existing senior, disability, and youth pass programs and have little appetite for introducing an additional administrative burden.

The most likely partners for the MBTA would be either the Massachusetts Department of Transitional Assistance (DTA), which administers food stamps, or MassHealth, which administers healthcare benefits. The general eligibility requirement for food stamps is most encompassing at 200% of the federal poverty level, MassHealth 138% of the federal poverty level, and public housing 80% of the average median income (Table 3.1). New York City's program uses 100% of the federal poverty line as the threshold (Fitzsimmons, 2019).

In thinking through the policy implications of my research, there is a trade-off regarding how restrictive to make the eligibility requirements. I took a conservative approach by conducting my study using the higher food stamps threshold. If a treatment effect is detected, it would be expected to be even more pronounced if the sample only consisted of those below 100% of the poverty level (the assumption being that those who earn less are more likely to exhibit a change of behavior). Seeing an impact on the larger population eligible for

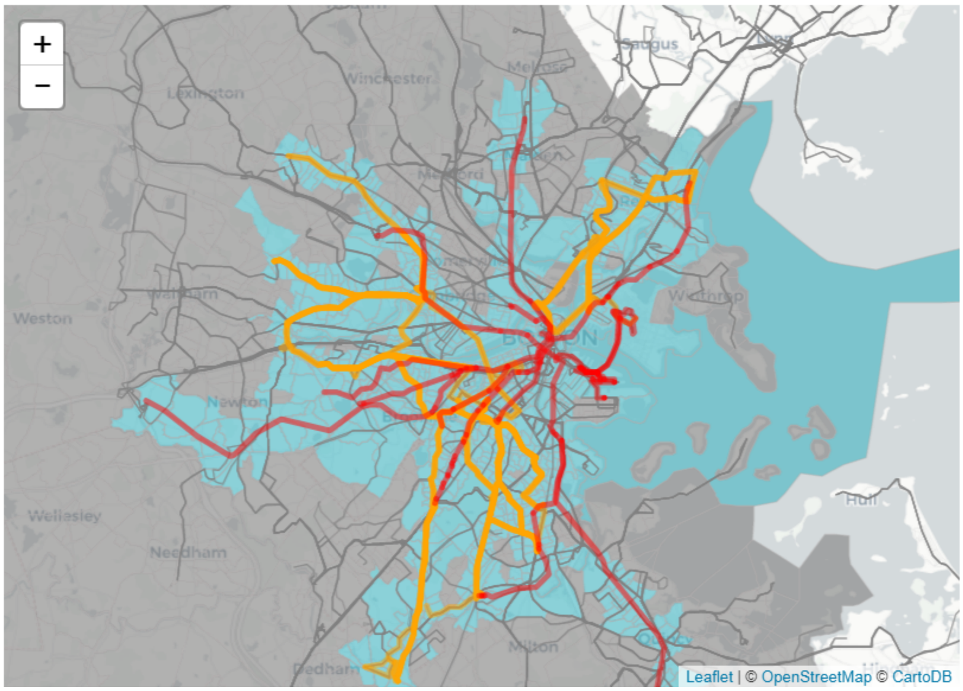
Table 3.1 Existing means-testing programs (Blynn 2016)

Metric	Household Income Threshold for Boston (family of 2)	Used by these social safety net programs
100% Federal poverty level	$16,000	N
138% Federal poverty level	$22,000	MassHealth/Medicaid
200% Federal poverty level	$32,000	SNAP (food stamps); Mass Rental Voucher Program
30% Average median income	$21,000	Section 8: Extremely Low Income
50% Average median income	$35,000	Section 8: Low Income; Other affordable housing
80% Average median income	$53,000	Public housing
85% State median income	$61,000	Temporary Assistance for Needy Families (TANF); Early Education and Care

food stamps is less certain, but such an impact would be more powerful. If a treatment effect was detected for individuals below 100% of the poverty level, the results would not be generalizable to the greater population eligible for food stamps. Policy makers are likely to choose more targeted aid, so would be wary of including a larger population if not warranted.

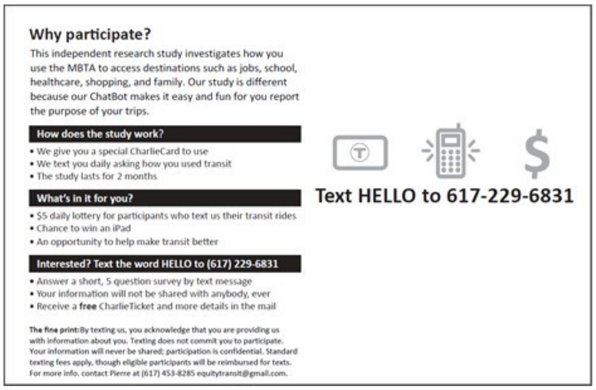
I developed an outreach strategy through a partnership with the Massachusetts DTA to access a pool of participants receiving food stamps benefits. Other organizations considered included MassHealth or the Boston Housing Authority both of which could, in theory, provide a random pool of participants. In addition be being designated as low-income, in this case receiving food stamps benefits, other criteria were used. I did not want participants who were already eligible for an existing discounted transit card program, such as seniors, persons with disabilities, and youth. The final criterion was proximity to transit such that using public transit was at least a potential option for them. Outreach was limited to individuals living close to a public transit stop. The DTA dataset was winnowed to only include only families with addresses within a quarter-mile of a high-frequency bus stop and half-mile of a rapid transit (subway) stop. Bus stops were included only if they are on one of MBTA's 15 *key* *bus routes* which have high ridership and higher frequency standards than other bus lines (Figure 3-17).

Figure 3-17 MBTA catchment area: half-mile to subway/light rail (the red lines) and quarter-mile to *key bus routes* (the orange lines)



In collaboration with the DTA, I mailed recruitment postcards to 12,000 individuals currently receiving SNAP benefits in the Massachusetts Bay Transit Authority (MBTA) core system catchment area. Figure 3-18 presents a copy of the postcard. I estimated that I would be able to enroll 5%, or 600 individuals, from the 12,000 postcards sent. When the actual response rate of eligible participants was looking to fall far short of expectations, I mobilized a plan to put 450 advertisement placards, very similar to the postcard, on buses. This increased the number of responses bringing the total number of fully enrolled participants to 242. To confirm that the participant was a food stamps recipient, individuals were asked to enter the last 5 digits of their food stamps card identification number or respond *none*. Though I had no way to confirm the validity of the responses, it did provide a higher level of confidence in their eligibility. Of the 1400 individuals who initially made contact with the ChatBot, 242 were successfully enrolled in the study representing a rate of 18%.

Figure 3-18 Outreach postcard design



Recruitment was a multi-step process. First, an individual initiated contact with the ChatBot and answered several eligibility questions. If eligible, they were sent additional information about the study and MIT's institutional research board (IRB) approved consent information (Appendix C). A link was sent by text message and email, and hard-copies were sent by postal mail.

Upon receiving materials, they would text the ChatBot to continue enrollment. The IRB permitted consent questions and answers to be administered by the ChatBot using the following three questions:

1. *Did you read and understand the informed consent form that you received? (y/n)*
2. *Do you agree that data you provide through text or special smart card will be kept confidential but used for research as described on the Informed Consent form? (y/n)*
3. *Are you aware that participation in this study is completely voluntary and you may stop at any time without penalty? (y/n)*

Demographic information was collected once consent was obtained. About 80% were never fully enrolled, some because they were not eligible and others because they did not complete the intake process. Summary statistics of the recruitment uptake are presented in Table 3.2.

Table 3.2 Enrollment statistics

			Number	Proportion
Total initial contacts-			**1403**	**100%**
Enrolled			242	17%
	postcard		126	52%
		control	63	50%
		treat	63	50%
	bus advert		116	48%
		control	58	50%
		treat	58	50%
Not enrolled			1161	83%
	postcard		329	28%
		ineligible	102	31%
		incomplete application	227	69%
	bus advert		832	72%
		ineligible	434	52%
		incomplete application	398	48%

Overall initial contacts		**1403**	**100%**
	postcard	455	32%
	bus advert	948	68%

Literature discussing study designs for working with low-income populations focused on the need to establish credibility and trust. Because these populations exhibit general skepticism of government agencies, I emphasized the research as independent in the outreach materials. Scoping interviews with community leaders working with low-income populations indicated that MIT would bring a level of trust. I obtained endorsements by the T-riders Union and the Mel King Institute, and communicated those endorsements in the outreach materials.

3.2.7 Political hurdles

Implementation of the project was initially planned for March and April 2018 but was met with a variety of political and legal roadblocks beginning in February 2018 which caused a one year delay. I invested significant time, energy, and political capital to overcome this hurdle. Being able to understand and determine how to work within the constraints of government bureaucrats is critical for developing robust partnerships, something I practiced extensively in my previous work as a transportation policy advocate.

In order to execute the project as designed, collaboration with two government agencies was needed: (a) with the MBTA, to obtain smart cards that functioned as discount cards and to have access to the usage data, and (b) with the DTA, to access their mailing list so as to send the targeted postcard mailing to a filtered list of food stamps recipients. An alternative to using special half-fare smart cards would be to reimburse participants at the end of the program. I did not believe this would provide a compelling enough real world experimental condition to have confidence in the results.

In February 2018 just as an agreement with the DTA was about to be finalized, a concern arose that some of the postcard language would be construed as offensive to the MBTA (Figure 3-19). I had carefully crafted the language because research suggests that a way to overcome challenges in connecting with marginalized populations is to build trust by not appearing naive about the problems faced. DTA wanted MBTA to "approve the language" on the postcard. In recent years, MassDOT and the MBTA have been creating an environment within their agencies regarding how they interact with academic researchers: "We don't approve research, we don't approve outreach or survey language." This in part came from the growth of the internal research, analytic, and policy capacity of the MBTA through the recent creation of the Office of Performance Management and Innovation. They feel this allows outside researchers broader freedom and insulates the agency from potential political conflicts. The problem was that the DTA did not have this same philosophy and, instead, wanted someone at the MBTA to approve the postcard language. The MBTA was not willing to make such a statement, leading to a roadblock.

Driving DTA's concerns was the politically sensitive nature of a low-income fare program.

Figure 3-19 Outreach postcard language before (left) and after (right) language

Why participate?
We know there are problems with the T: rising fares, frequent breakdowns, and buses that don't come often enough or take you where you want to go. Information about how you use buses and subways is a powerful tool to show that things need to change.

Why participate?
This independent research study investigates how you use the MBTA to access destinations such as jobs, school, healthcare, shopping, and family. Our study is different because our ChatBot makes it easy and fun for you report the purpose of your trips.

Early 2018 coincided with a Massachusetts gubernatorial election year. The DTA and MassDOT were under pressure to avoid anything politically controversial. The concern was the chance that one of the outreach postcards would be obtained by the media prompting a request for the Governor's office to provide an opinion on low-income fares. Despite the high likelihood of reelection at the time, the Governor did not want to be forced to discuss this issue in public. After six months of significant networking, I was finally able to convince MassDOT to take the lead in obtaining the necessary political approvals.

A subsequent hurdle unexpectedly presented itself when trying to get a *Memorandum of Agreement* signed between MIT and the DTA. One issue was MIT would not permit MIT students to sign a confidentiality agreement for coming into contact with names and addresses of SNAP recipients. The DTA office agreed to not require such signatures. The larger more complicated dispute had to do with the standard confidentiality language DTA required to be included but MIT would not agree to: "MIT understands that the name and address of SNAP recipients is considered 'personal data' and the parties are holders as such as defined in M.G.L. c. 66A. The parties must comply with all federal and state laws and regulations applicable to the data, including but not limited to 7 CFR 272.1(c), M.G.L. c. 66A, M.G.L. c. 93H, and M.G.L. c. 66, § 17A." Even though participants voluntarily signed up for the study and provided their contact information in response to receiving the postcard, we would know they are SNAP recipients. DTA therefore considered their rules applicable. MIT, on the other hand, believed that the referenced regulations did not apply to us—by signing a document with those references included, MIT believed they were agreeing that they did indeed apply. DTA was not willing to just say "must comply with all federal and state laws and regulations applicable to the data" and eliminate the "including" clause. After a significant amount of internal wrangling within MIT by our designated contract administrator from the Office of Sponsored Programs, MIT agreed to accept DTA's language. Finally, on December 10, 2018, the Memorandum of Understanding was signed and countersigned, concluding a three-month process. The MOU is provided in Appendix B.

3.2.8 Implementation

I began recruiting participants in January 2019 and ran the experiment from February through May of 2019. Individuals recruited through the postcard all participated for the months of February and March. Individuals recruited by bus advertising participated for two months on a rolling basis beginning in either February, March, or April. Participation always began on the first of the month such that individuals would have time to purchase a monthly pass if they desired.

I randomly assigned half (121) of the participants to the treatment group that received a discount smart card and half to the control group who received a regular smart card (Figure 3-20 shows an image of the card provided). Those recruited through the bus advertising were alternately assigned to the treatment and control groups once they completed enrollment.

Figure 3-20 Sample of a smartcard provided to participants.

The intake survey, conducted by text, included several demographic variables to assess study arm balance and as covariates in regression analyses. These questions are listed in Table 3.3. Summary statistics of the two groups are shown in Table 3.4. For the demographic variables collected and the distribution of self-reported health, there is no indication that there is a statistically significant difference in the balance of the control and treatment groups.

Table 3.3 Pre-study intake survey demographic questions

Demographic covariates
Preferred spoken language
Age
Gender
Do you work full time, part time, or not at the moment?
What race or ethnicity do you consider yourself?
How many children live with you?
Do you currently consider yourself a single parent?

Through a collaborative partnership, the MBTA provided discounted smart cards that deduct half the regular fare for each use or allow for the purchase of a $29 monthly pass.

Table 3.4 Summary statistics of the two study arms

	Control (n=121)	Treat (n=121)	
	Mean	Mean	p-value
Age	36.2±12.1	37.3±11.8	0.29
Male	22%	17%	0.31
Female	76%	82%	0.23
Black	38%	41%	0.62
Hispanic	16%	11%	0.24
White	31%	31%	0.97
Other	15%	13%	0.64
Employed full	22%	18%	0.42
Employed part	35%	34%	0.87
Unemployed	43%	48%	0.41
Single Parent	54%	62%	0.19
Not-single-parent	46%	38%	0.19
English	96%	93%	0.29
Spanish	4%	6%	0.65
Chinese	0%	1%	0.25
For age, p-value calculated using unpaired 2-sample t-test			
For other parameters, p-value calculated using Pearson's chi-squared test			

The discounted monthly pass costs $29 compared with the standard unlimited monthly pass which costs $84.50. Ordinary smart card users can also purchase a weekly pass for $21.25 but because of limitations with the MBTA's existing Automatic Fare Collection system, a weekly pass option is not available for discounted smart card users. Each smart card came with the equivalent value of two free rides to encourage initial use. Participants were responsible for adding value or a pass to their card. Participants were provided email, phone, and texting contact information to obtain help during the study for issues such as a lost smart card, change in phone number, or new address. A smart cards was sent to each participant with an accompanying letter customized for control and treatment group participants. An insert provided instructions for responding to the daily travel diary. A refrigerator magnet with contact information for the researchers was included. Samples of these mailings in English are provided in Appendix C.

Trip data came from MBTA's Automated Fare Collection system which records all instances when a smart card interacts with the MBTA system. Each time a smart card is used to pay for a trip either at a station of on a bus, the transaction linked to that card is stored. Likewise, transactions adding money to smart cards are recorded. The MBTA pre-processes this data incorporating Automatic Vehicle Location data to determine detailed trip information (Gordon, Koutsopoulos, Wilson, & Attanucci, 2013). For a transit system like the MBTA where there is only *tap-in* and not *tap-out*, it is necessary to infer the destination when possible.

The ChatBot was also used to automate the collection of daily travel diary information from each participant with respect to the purposes of their transit trips. Each morning at 9:00 am, the ChatBot automatically sent a text message to each participant requesting a reply with a trip purpose travel diary from the previous day: *Reply with the purposes of all MBTA trips you took yesterday (or say none).* Based on preliminary testing, it was decided that a natural language response would be easier and more flexible for the participant. To encourage participation in the program, each day that a participant answered the ChatBot travel diary they were entered in a $5 lottery with multiple winners picked each day. Taking a transit trip was not a requirement of entry as participants could respond with *none*. The chance of winning the lottery was about 3% each day such that is was likely that each participant would win at least once over the course of the study.

3.2.9 Addressing bias

In studies like this, there exists a multitude of potential conditions that could bias the results. The most critical ones are discussed below: equivalent composition, differential attrition, and participant self-selection. Sample attrition is a pervasive issue for surveys in social sciences. The damage appears particularly clearly in randomized trials: while random assignment to treatment creates a treatment group and a control group that are at the same time comparable and representative of the initial population, in the presence of sample attrition, however, the observed treatment and control groups may not be comparable anymore, threatening the internal validity of the experiment.

Dropout in longitudinal randomized controlled evaluations is common and a potential source of bias. Because measurements were being made continuously from two different data sources, the smart card and the ChatBot, there is not a straightforward measure of attrition. Instead, a metric was used for the number of days until the last response to the ChatBot was detected for each participants.

As mentioned earlier, recruitment was conducted without participants knowing ahead of time that they had the possibility of receiving a discount card. The study was designed with the ChatBot daily travel diary and daily $5 lottery draw as the primary incentive for continued participation. Individuals chose whether to respond to the call for participation and ultimately whether to participate which may have led to a self-selection problem. The concern is one of generalizability if the sample does not represent the target population for the eventual policy intervention.

Because the control group did not have the same incentive as the treatment group to always use their designated smart card, there is the potential that participants in the control group sometimes used an alternate smart card. We would expect the treatment group, on the other hand, to be more likely to always use the study's smart card because of the discount it provided. To mitigate this concern, we asked participants prior to the study to provide the serial numbers for any smart cards they were currently using. We monitored these cards and applied these trips to the participant's data. In addition, we applied special labels on the back of the study smart cards to help participants distinguish it from other cards and make it feel more special than an ordinary smart card.

Individuals in the treatment group might share their card with others which would bias the results. To mitigate, we asked each participant in this group, at the conclusion of the study, how frequently they shared their smart card (to encourage an honest response, we also told them it was not a problem if they did share their card). Only 5% indicated that they shared their card and the majority of those who said they did indicated that they did so infrequently. Surprisingly, this 5% was evenly distributed between the control and treatment groups. This result was triangulated through qualitative interviews which also found that few shared their card and those who did said they did not do it often. Though attempts were made to measure this potential bias, it is challenging to conduct such measurements with confidence.

3.3 Semi-structured interviews

Lindblom warns that there is no such thing as a *science of society* that can guarantee the existence of correct answers to societal challenges, that an overly rational, scientific planning approach to incredibly complex systems is a seduction (Lindblom, 1992). As such, interviewing individuals who would be directly affected by a potential policy intervention crucial in contributing to an understanding of the implications. "There is little transit related research that is informed directly by riders, especially low-income riders, suggesting the conventional approaches to understanding how riders afford the fare are incomplete (Perrotta, 2015)." The participant interviews were designed to better understand how individuals make decisions regarding utilization and payments for public transit in light of prior research done by others and the findings from the randomized experiment. The areas of focus for the interviews are discussed below. A copy of the interview protocol is included in Appendix D.

- *Scarcity mindset.* An overarching objective of the interviews was to test the behavioral science theory that scarcity hinders cognitive function and therefore decision making.
- *Barriers to transit.* The literature on fare elasticity and affordability debates whether

the barrier is mostly the fare or aspects of service quality such as reliability, frequency, and routing. As the results from the randomized experiment suggest that fare is indeed a factor, the interviews were used to identify evidence in support (or refutation) of this finding.

- *Forgone trips.* Of particular interest is what types of trips are being forgone to better understand the impact on accessibility. I decided to focus on accessibility to healthcare. Income-based disparities in health outcomes and the concerns with appropriate access to care are discussed in the literature as important, and the randomized evaluation found a statistically significant average treatment effect on the number of healthcare trips taken.

- *Paying by pass or per trip.* At the outset of the research, I had a hunch that the decision as to whether or not one purchases a pass has an important influence on travel behavior. The study findings indicated that 30% of participants did not purchase a weekly pass when it would have been beneficial to them. Therefore, during the interviews, I aimed to better understand how these decisions are being made.

- *Fare evasion.* An analysis of cash payments on buses revealed that 60% of cash paying customers underpay. Based on this finding, I incorporated related questions into the interview protocol to identify evidence that this behavior is in response to issues surrounding affordability. Better understand fare evasion behavior is also important in the context of planned upgrade to the automatic fare collection system which will include a proof of payment system instead of the current practice where bus drivers monitor fare collection. The implication is that individuals will no longer be able to underpay in the same fashion as they can today.

- *Impact of the fare subsidy.* For those in the treatment group, I aimed to better understand the participants' reflections on how they perceived any changes to their behavior while participating in the study and when it ended.

- *Reactions the ChatBot.* At the outset of the research, I was unsure how participants would respond to the ChatBot. Participation rates were high during the pilot implementation, and were also high for the randomized study. During the interviews, I asked participants to reflect upon interacting with the ChatBot during the study.

I established several criteria for selecting participants to interview. For the issue of paying by pass or per trip, I filtered for individuals who took enough trips that it was reasonable to expect them to be thinking about whether or not to purchase a weekly pass, so taking more than 9 trips per week (95 participants). To have a meaningful conversation regarding healthcare trips, I filtered for participants who indicated taking at least five healthcare trips per month over the course of the study (89 participants). I then had two lists to choose from (32 participants fit both of these criteria.) I created a panel of participants to interview by selecting individuals from each of the two groupings. The selection to represented a cross section on the demographic characteristics of age, race, gender, and work status as well as home location.

I reached out to participants by text to set up interviews in small batches. The response rate was high, with over 75% of participants replying to the initial text. Of those who responded, I was able to set up interviews with 80% of them. As I progressed with reaching out to subsequent batches of participants, I adjusted the requests to maintain a reasonable cross section for the demographic characteristics. I conducted the interviews in semi-public locations easily accessible by transit. The types of locations included community rooms at local banks, tables in the lobbies of a public buildings, conference rooms at a local neighborhood organizations, library meeting rooms, and cafes / donut shops. Each interview lasted approximately 60 minutes. I provided $20 cash for each participant to thank them for their willingness to be interviewed. In all, I conducted 20 interviews.

3.4 ChatBot

Data collection is a challenging aspect of real world experiments. There are many approaches to constructing a study sample. I designed this project such that most interaction with participants was done through automated text message. This leveraged two important aspects of the study. It automated the participant recruitment process to obtain a large enough sample size for the experiment with minimal amount of labor. It enabled collection of daily travel diary data on the purpose of transit trips taken by participants. While smart card data provides the number of trips taken by participants, it does not provide information about the purpose of those trips.

With significant mobile smart phone penetration in today's world, many researchers and consultants have developed apps for such purposes. Few reasonably priced off-the-shelf app development platforms are available and non met the specifications for my project. Designing a customized app from scratch is challenging given the need to accommodate various devices, screen sizes, and operating systems. In addition, mobile phone users' concerns for security, privacy, and battery life associated with third-party apps. In addition, low-income individuals are less likely to have consistent internet connectivity.

Given the constraints above, I decided to utilize a texting approach for my project. Within the last several years, several companies began providing affordable services to process text/SMS messages between users and custom designed software making this approach viable. As such, I custom designed and built an automated ChatBot texting tool.

This section starts with an overview of the current state of practice regarding conducting travel surveys as well as how researchers have used emerging smartphone technology as a way to interact with study participants. Problems with travel diary type outputs from smartphone apps are discussed. I then provide an overview of the ChatBot software architecture and implementation. I conclude with an evaluation of the response rate. I compare this response rate with those from two independent projects by other researchers whom used a modified version of my ChatBot software.

3.4.1 Background

Urban transportation modeling, analysis, and forecasting relies on travel behavior as a key input. Household travel surveys have been the primary mechanism used to collect such data and have been around since the 1940's (Weiner, 2013). As technologies improved over time, so did methods to collect survey data. Along with these changes came debate over the pros and cons of each. Originally, randomly selected in-home interview methodology was used to obtain origin-destination surveys. Later, mailed surveys were introduced. In the 1970's, random digit dialing phone became a popular method. The advent of the internet paved the way for web-based survey methods. But the most significant developments have only occurred recently now that mobile phone penetration rates are high enough and demographically distributed enough to provide valid results. Apps allow for a combination of passive and active data collection from users. One major leap with mobile technology is the ability to track and engage individuals *in situ* as they go about their daily lives. GPS permits such passive mobile phone location tracking. Customized apps and automated text messaging permit direct engagement with participants in ways unfathomable just a decade earlier. The precipitous decline in landline phone usage has made traditional phonebook-based surveying obsolete. Though still used, obtaining responses from random dialing of mobile phone users has become increasingly challenging because of the rapidly rising sophistication of marketing and spam callers.

Travel diary collection techniques have developed significantly alongside the rise of mobile technologies. The first innovation was GPS-enabled wearable devices designed specifically for such a purpose. Now, mobile phone technology has expanded potential surveying options significantly. Using mobile phones as a survey instrument has been receiving significant attention over the past decade. Customized apps is one way to engage with users (Li et al., 2017). With a flexible programming environment, dynamic survey features such as *memory joggers* and *prompted recall* assist participants in recalling what happened on the assigned day at the specific location utilizing the GPS trace (Stopher & Greaves, 2007). Survey systems can now infer activities and destinations and then ask users to verify the information, reducing the load on the user and improving reliability of the data.

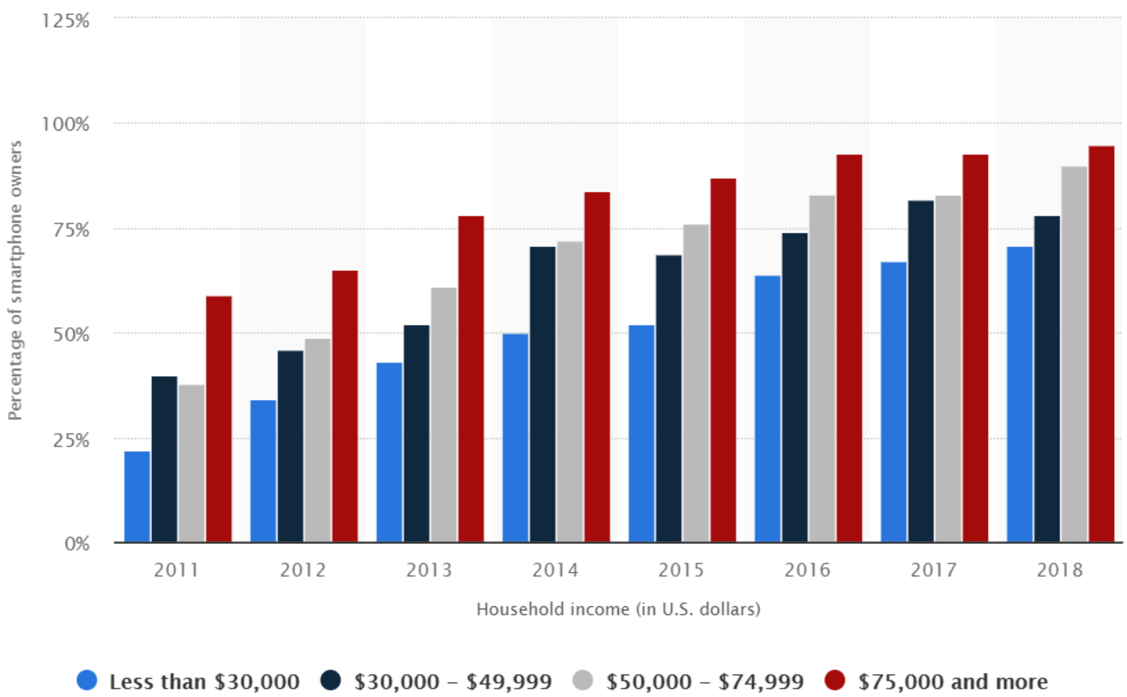
Newer modeling methods also require more robust data, namely activity-based models. These models come in two forms: the tour based model focuses on the generation of the individual trips that compose a full activity tour, and continuous time activity-based model focuses on the time and duration of the place-based activities (Pendyala et al., 2012). Both models require a synthetic generation of households' travel demand and subsequent behavior. More detailed understanding of these behaviors is then needed. Activity scheduling becomes an important part of the model and therefore requires a more intricate understanding of individual travel decisions. Recognizing increasingly dynamic travel patterns, multi-day surveys and longer term longitudinal surveys provide higher quality data. Awareness is growing among researchers that travel behavior is far more dynamic than is typically captured with existing survey methodologies (Doherty, 2006).

Smartphones have significant potential to further these research objectives. The operating system platforms allow for development of highly intuitive and user friendly interfaces, and these devices also contain a variety of sensors and have impressive computational power. However, there are several downsides with the current smartphone ecosystem. Programming that ensures robust software operation across multiple platforms and operating systems is among the greatest challenges. Though barriers to entering app development are lower than ever, a focused product development workflow to ensure a reliable product is required. There are also issues surrounding the adoption and use of apps by participants. Potential participants may be unwilling to install the app because of concerns about storage space, battery life and privacy (Hoch, 2015). Though the smartphone ownership rate for low-income individuals is now very high approaching that of those who are wealthier (see Figure 3-21).[11]

[11] 71% of Americans with household incomes below $30,000 a year own a smartphone, 64% have internet at home or a computer compared with those with annual household incomes of over $100,000 where over 97% own a smartphone and 90% own a computer. The 71% in 2019 is up from 20% in 2011. (See https://www.pewresearch.org/fact-tank/2019/05/07/

Low-income individuals, though, often have unreliable access to wifi or data plans which interfere with surveying instruments that require real-time engagement (Smith, 2015). Another user concern is the heavy battery consumption required for many apps that use GPS regularly. Developing a power-efficient app is a challenging programming exercise. Large surveying consulting firms have heavily invested in developing and refining apps that are battery efficient.[12].

Figure 3-21 Percentage of U.S. adults owning a smartphone from 2011 to 2018, by household income.



Source: https://www.statista.com/statistics/195006/percentage-of-us-smartphone-owners-by-household-income/

A number of factors may impact the reliability of the survey results. One is that a random outreach scheme might lead to a non-random sample of willing participants by introducing exogenous factors. Another is the rate at which participants engage in the survey if it is

digital-divide-persists-even-as-lower-income-americans-make-gains-in-tech-adoption/).

12 See, for example, *rMove* by RSG https://rmove.rsginc.com/

involves a longitudinal design. For travel diaries that rely on a complete set of data for a particular time period, such as a week, missing pieces are problematic. A third is incomplete or erroneous responses. A respondent might participate but report no travel on days where there was travel to reduce the reporting burden, sometimes referred to as *soft refusal* (Madre, Axhausen, & Brög, 2007). It is common for individuals to omit (or forget) trips or activities that lasted for a short period of time, and the longer the delay between the event of interest and the survey response request, the higher the likelihood of misremembered activities being reported (Axhausen & Rieser-Schüssler, 2014). The lack of ground truth hinders the ability to evaluate the quality of survey results.

In reviewing the literature, I did not identify any previous research using text messaging to obtain travel diary information. There have been some applications in the urban planning field for conducting surveys (Hoe & Grunwald, 2015). The health profession, though, regularly employs texting/SMS engagement with patients and clients primarily to *nudge* them toward healthier behaviors such as exercise, weight loss, cardio-vascular disease, glycemic control for diabetics, binge drinking, depression, smoking, and sleep habits (Woo, Chen, & Ghanavati, 2013). Most recently, texting has become a very popular mechanism for companies to provide customer support.

Surveys have long been questioned for their accuracy in recording the information they purport to collect. For example, respondents might be bored, unmotivated, or not understand the directions, thus omitting or providing erroneous information (Bonsall, Schade, & Roessger, 2011).

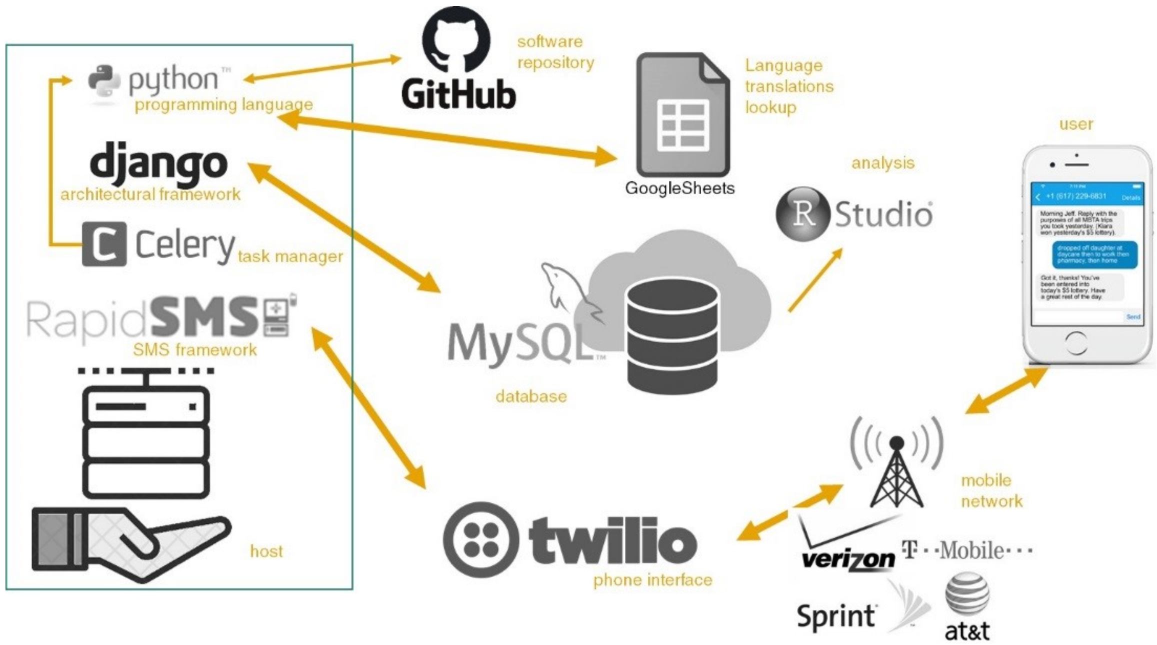
With the availability of more powerful analytic tools, researchers are more robustly investigating survey response patterns to understand discrepancies between actual responses and intent. Mobile phone tower triangulation records allow for the anonymized analysis of mobility patterns and transit fare collection systems provide similar aggregated data on origin destination travel behavior.

3.4.2 Software design

The ChatBot tool was developed to automate three aspects of the project: (1) recruitment and Institutional Research Board required participant consent, (2) the pre- and post-survey questions, and (3) daily travel diaries of participants used to measure accessibility by asking about trip purpose. Early in the project development, I used an online service, `Motion.ai`, which had a nice visual builder interface and integrated connection to text messaging/SMS. Unfortunately, when that company was purchased by HubSpot the text/SMS enabled service was not immediately available. `Motion.ai` went out of service in December 2018, just prior to my project's launch, which was quite unfortunate especially because the project should have been executed in early 2018 or by fall 2018. Knowing the pending shutdown in advance, I was able to partner with the MIT Undergraduate Research Opportunities Program and work with a freshman computer science major to assist in the development of a ChatBot application from scratch. A summary of the software components is shown in Figure 3-22.

To automate the enrollment and consent process, the ChatBot software tool engaged with potential participants solely by SMS/text message. Conversation flows were constructed and modified in JSON format for the ChatBot to parse. Data was stored in a secure MySQL database. With SMS/text messaging, there a participant can use a *dumb phone*, does not need to download a specialized app, and does not need access the internet. The ChatBot was programmed generically to allow for flexible implementation in many languages. When an individual first contacted the ChatBot, they were asked for their preferred language chosen from English, Spanish, Vietnamese, and Chinese. The ChatBot would then converse with the individual in that language. Additional details about the study and the consent form (in the selected language) were sent by email and postal mail. The Institutional Research Board

Figure 3-22 ChatBot components

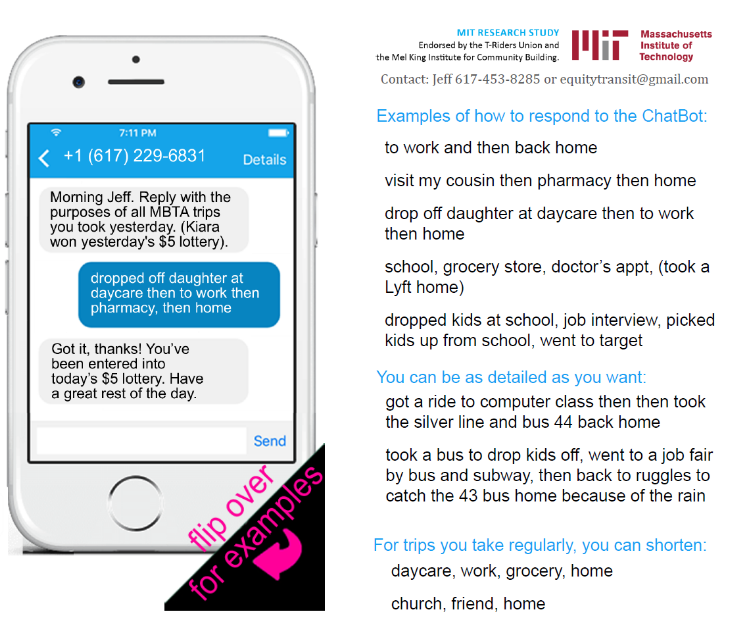


permitted the consent process to be completed by the ChatBot which positively impacted the participation rate. Participants granted permission to track the usage of their smart cards.

3.4.3 Evaluation

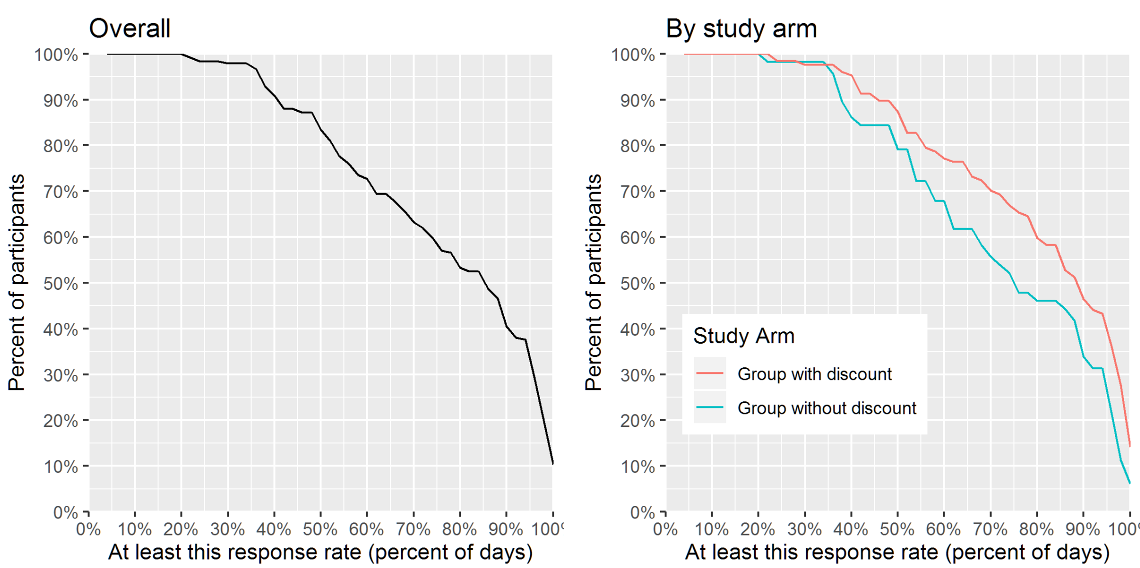
Overall, participants collectively provided about 7200 ChatBot daily diary responses. On average, participants responded to the daily ChatBot requests 73% of the time, a much higher response rate than was expected. However, the average response rates differ by group with the control group responding on average 66% of the days while the treatment group 77%. Figure 3-24 presents this data as a reverse cumulative distribution describing the percent of participants who have a response rate at least as high as the value on the x-axis. 72% of participants in the control group and 85% of the treatment group responded to at least 50% of the ChatBot diary requests. This difference is a potential source of bias in the tallying of

Figure 3-23 Screenshot of the ChatBot travel diary along with the information sheet provided to participants.



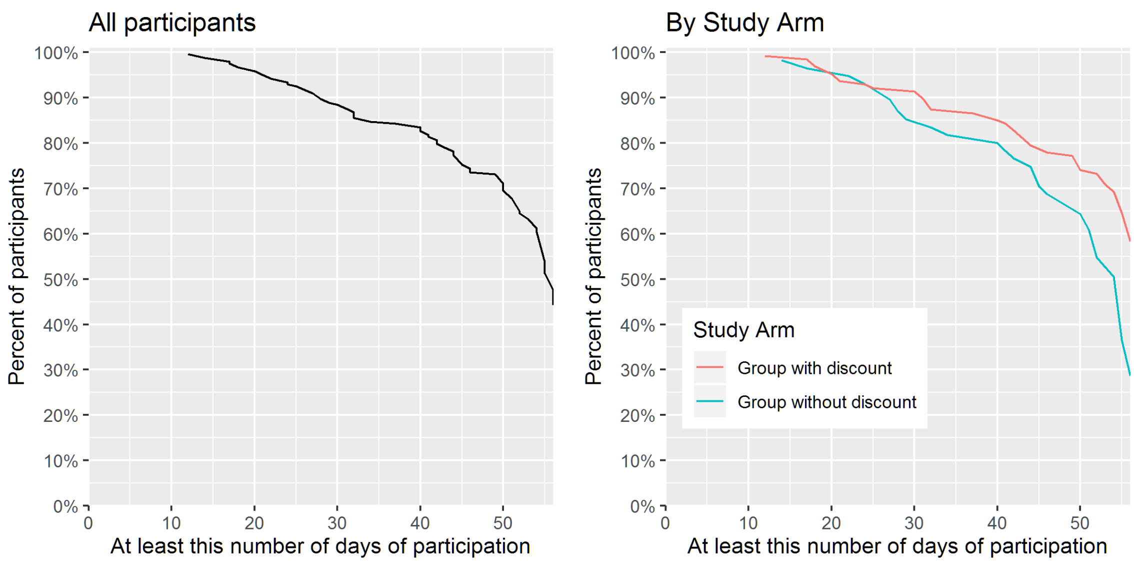
trip purposes.

Figure 3-24 Participant response rate to the daily ChatBot (reverse cumulative distribution)



About 70% of the treatment group participants maintained engagement with the ChatBot travel diary throughout the entire study and 45% of the control group (Figure 3-25). This suggests that the treatment group participants were more engaged in the study which could be a source of bias regarding the analysis of trip purpose, with the true total number of trips by trip purpose under-reported for the control group. To partially compensate, the rate calculations for trips per month were performed by dividing the number of trips in each category by the number of days in the ChatBot participation period for each participant.

Figure 3-25 Duration of participation (reverse cumulative distribution)



3.4.4 Extensions

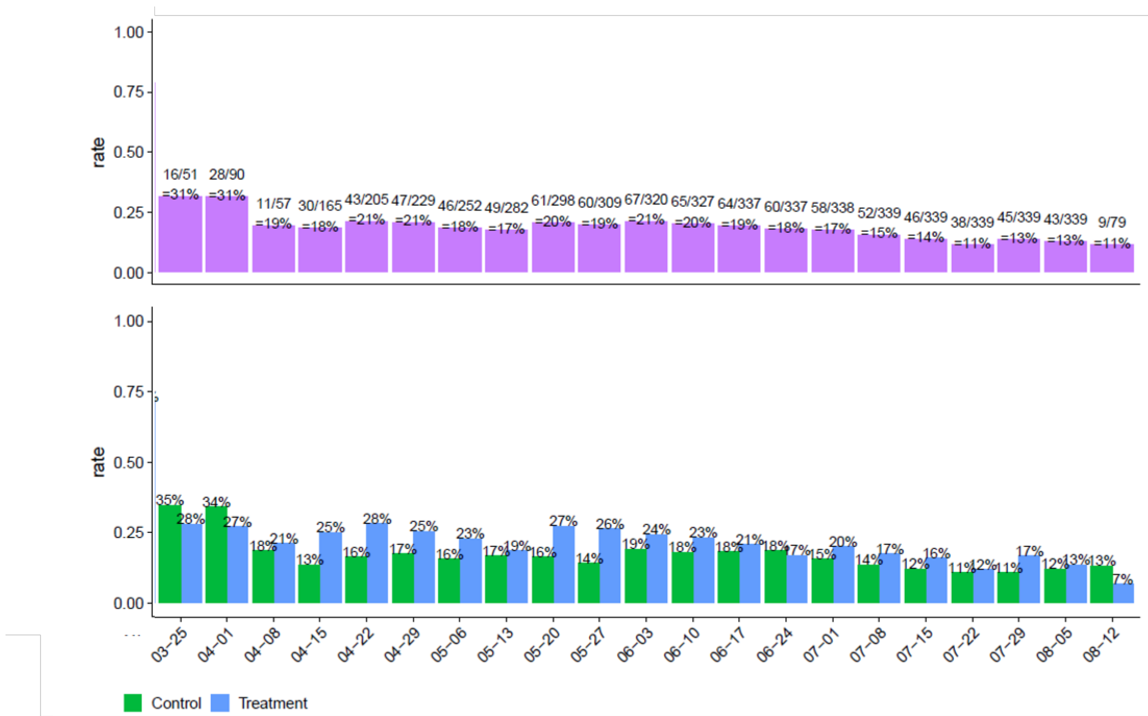
Several other academics reached out to me expressing interest in utilizing the ChatBot as a survey tool for some aspect of their own research. I engaged in two collaborations helping design and refine the survey instrument and implementing ChatBots for each. Though the projects utilized the ChatBot in a different context, weekly surveys, I was able to utilize the core of the existing ChatBot software with relatively few modifications. Both projects were engaging with low-income populations and both happened to also be randomized controlled evaluation studies. I used these two additional projects as comparative case studies, and I used the response rate as the comparative metric.

Notre Dame/ Seattle. A team of researchers from Notre Dame University are studying the impact of free-fares compared with half-prices fares for low-income public transit riders in Seattle using. Participants were recruited through a partnership with the food stamps office where counselors enrolled interested participants when they signed up for food benefits. Users set their language preference when they first registered. The ChatBot could operate in any of the following languages: English, Spanish, Vietnamese, Chinese, Arabic, Korean, Russian, Somali, and Tagalog. The intent was for participants to initiate contact with the ChatBot immediately with the case worker, but a research could manually enter them into the system if they did not do so themselves. About half of the participants were entered manually, meaning their language was set to English as default. Of the 180 participants who selected their own language, all chose English except for Spanish (4) and Vietnamese (2).

The purpose of the ChatBot survey was to ask several questions once a week about the last trip taken. The design involved sending the text message survey request at pre-determined randomly assigned day and hour. Every Sunday, the ChatBot would automatically assign each active participant a random day of the upcoming week and a random hour between 9:00am and 8:00pm. Over the course of the week, the ChatBot would automatically initiate a participant's survey at the designated time. One of the key objectives was to determine the extent to which participants' use of the smart card was under-reported because they paid with cash or traveled using a different mode. Similar to the MBTA study, participants who responded to the ChatBot were entered into a lottery for a $5 Safeway (grocery store) gift card. Preliminary analysis indicated the response rate was far lower than that in the MBTA study (see Figure 3-27.) The response rates was about 17% with a slightly smaller percentage completing all four questions. About half who did participate responded between

35-100% of the time, and half under 35% of the time.

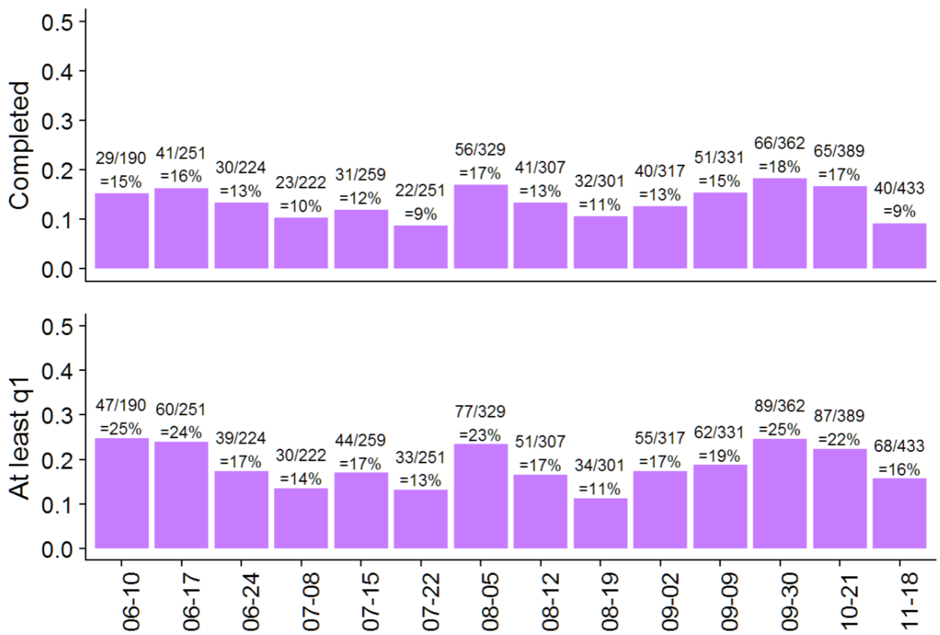
Figure 3-26 Notre Dame/ Seattle, WA: Preliminary analysis of participant response rate to the weekly ChatBot completing at least question 1



* * *

MIT/Boston Housing Authority. Researchers from MIT partnered with the Boston Housing Authority to testing the effectiveness of a new program to assist new voucher holders in their housing search process. The purpose of the ChatBot tool was to get feedback from participants on their housing search. The survey was initiated about every other week on Monday mornings asking about their search the previous week. Participants were incentivized to respond by being entered into a lottery for a $10 Stop & Shop (grocery store) gift card. The study began in June 2019 and is ongoing with new participants joining the study several times a month. Overall, eight questions were included in the survey, asking things such as self-reported perception on the the progress with the housing, the number and locations of residences for which landlords were contacted, and any challenges encountered with the search process. The average response rate was about 13% for answering all questions and 18% for answering at least the first question (Figure 3-27). The lower completion rate for the BHA study compared with the Notre Dame study may be related to its longer survey length.

Figure 3-27 MIT/Boston Housing Authority: Participant response rate to the periodic ChatBot survey



Note: The bottom bar chart indicates the percent who answered at least one question. The top bar chart indicates the percentage who completed the entire survey.

Figure 3-28 provides a summary and comparison of the three implementations of the ChatBot. While the 73% average response rate was far higher than expected for my experiment, the $17 - 18\%$ response rate for the other two experiments was disappointingly low. One hypothesis is that, for my study, there was a significant amount of back and forth during recruitment which built a rapport and level of trust between participant and researcher. Another hypothesis is that participants knew at the outset that texting was an integral part of the study. This could, though, suggest a selection bias for my project where those who were comfortable texting opted in at higher rates.

Even with the lower than desired response rates, researchers from the other two projects found significant value from the tool. The Notre Dame/Seattle project researchers were able to understand how the treatment induced mode substitution, and Boston housing project researchers were able to compare where the two study arms were looking for housing and what they considered obstacles to their search. Overall, the ChatBot has proven to be a valuable yet inexpensive tool for engaging low-income participants in research studies.

Figure 3-28 Summary comparison of key characteristics of the ChatBot implementations across three projects

Project	Participants	Purpose	Frequency	Lottery incentive	Response rate
J. Rosenblum (MIT) Boston: Randomized evaluation of discounted fares	Low-income individuals who receive food stamps (SNAP) benefits. Recruited from postcard and bus advertising.	One question on trip purpose	Daily	$5 cash	73%
D. Phillips (Notre Dame) Seattle, WA: Randomized evaluation of free fares compared with 50% discounted fares	Low-income individuals who receive food stamps (SNAP) benefits. Recruited at SNAP enrollment locations by councilor on staff.	Four survey questions about transit use	Weekly	$5 Safeway grocery gift-card	17%
N. Kelly (MIT/ Boston Housing Authority) Boston: Randomized evaluation of computer-based support tool to expand opportunities to Section 8 housing.	Individuals currently in homeless shelters who have been provided with housing vouchers.	Eight survey questions about housing search process	Bi-monthly	$10 Stop & Shop grocery gift-card	18% (13% answered all questions)

4

Travel behavior

This chapter describes the mobility patterns of low-income riders compared with that of the average transit ridership population. Though the advent of "big data" in the transit planning realm has led to significant analytical improvements in understanding ridership behavior, analysis is predominantly conducted on an aggregate basis because there is not a mechanism to connect income and other demographic information with smart card serial numbers. Making the assumption that low-income riders behave similarly to everyone else is dubious. With equity and justice a crucial component of transit planning decision making, this leaves an unfortunate information gap. Passenger surveys are one source of demographic, travel, and fare payment data. Alternatively, census data can be used in combination with geographic information- an approach commonly used for equity analyses.

The dataset of transit riders generated through my study enables analysis of low-income rider behavior including time-of-day travel, mode use, transfers, and travel time. Such analyses augment what can be done using census or typical passenger survey data. Once a set of smart cards can be tagged as belonging to low-income riders, travel behavior can be compared with that of overall riders by using data from the automatic fare collection system.

4.1 MBTA Travel Survey

This section uses the latest MBTA passenger survey to better understand how income correlates with various transit travel behaviors. The most recent MBTA survey was conducted between 2015 and 2017 through a combination of online forms and paper forms with a mail-in option distributed at MBTA stations and on board MBTA vehicles. Responses were collected at the route level for bus and ferry routes and at the station or line-segment level for all other modes. Each method generated approximately half of the total responses.[13] The sample size was was set in order to obtain a confidence level of 90 percent. To compensate for differences in response rates when comparing results from different lines or modes, the published results for each route, route group, station, or station group are weighted based on recent count data in proportion to typical weekday total passenger boardings on the corresponding services. Limited analyses has been conducted thus far that segment by income. It is important to note that 21% of all survey responses did not provide information about income, so those are excluded from the analyses below.

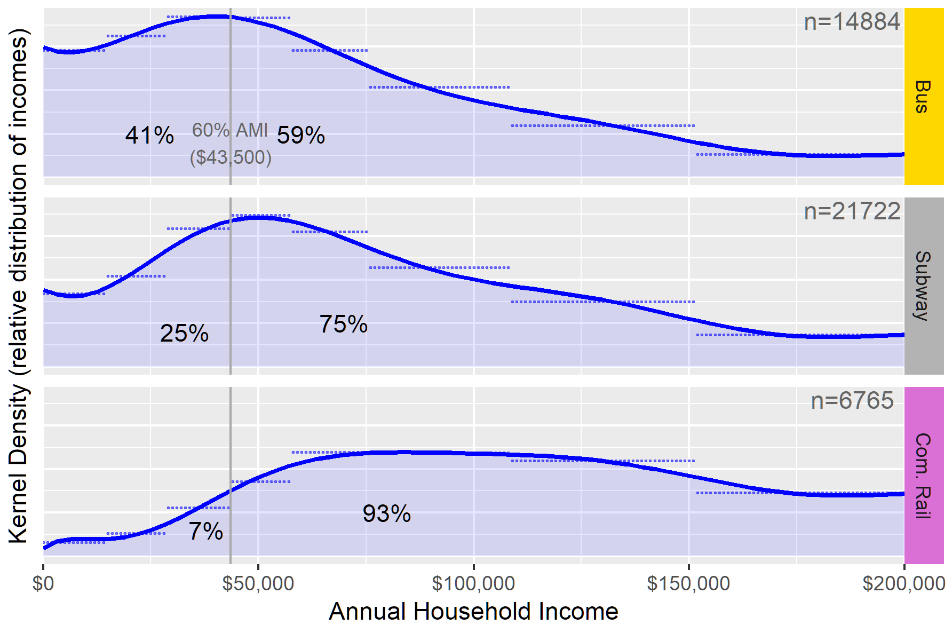
Mode. Differences in travel behavior by mode choice is an important element of equity. For this analysis, *low-income* refers to individuals with a household income of less than $43,000, corresponding to the first three income categories on the survey. Figure 4-1 shows the relative number of individuals in each of the household income categories along the x-axis. 41% of bus riders are considered low-income, 25% of subway riders, and 7% of commuter rail riders. Boston is similar to other cities nationwide with a larger proportion of bus ridership comprising those with lower incomes. The national average is 65% bus, 23% subway, and 27% commuter rail.[14] Overall, the MBTA has a higher percentage of higher-income bus

[13] A copy of the survey can be found here: https://www.ctps.org/apps/mbtasurvey2018/mbta_survey_English.pdf. On each of the plots in this section, N indicates the number of records in the dataset where a response was provided.

[14] Calculated from the 2009 National Household Travel survey for urban areas.

(60%) riders than the national average (35%).

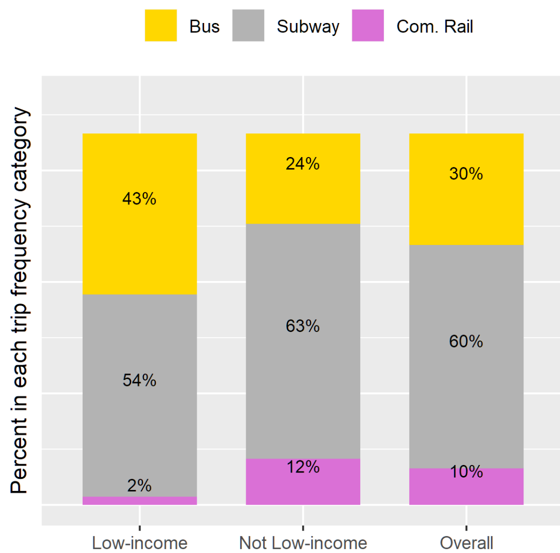
Figure 4-1 Distribution of MBTA riders by income and mode



Source: MBTA 2015-2017 Ridership Survey. **Notes:** This graph was generated by fitting a line through the step function of the ordinal data (dotted lines). Because the last income category was >$150,000, it was challenging to determine the end point for the kernel density distribution graph, in this case $200,000 was used. The vertical line is placed at $43,500 representing 60% of average median income. The percentage numbers on the left and right of that line indicate the percent of riders considered *low-income* and *not low-income* respectively.

Figure 4-2 shows this information by income category. Here, 43% of low-income individuals ride the bus while only 24% of higher-income individuals ride the bus. This is later compared with similar statistics for respondents in the study.

Figure 4-2 Number of trips by mode based on income

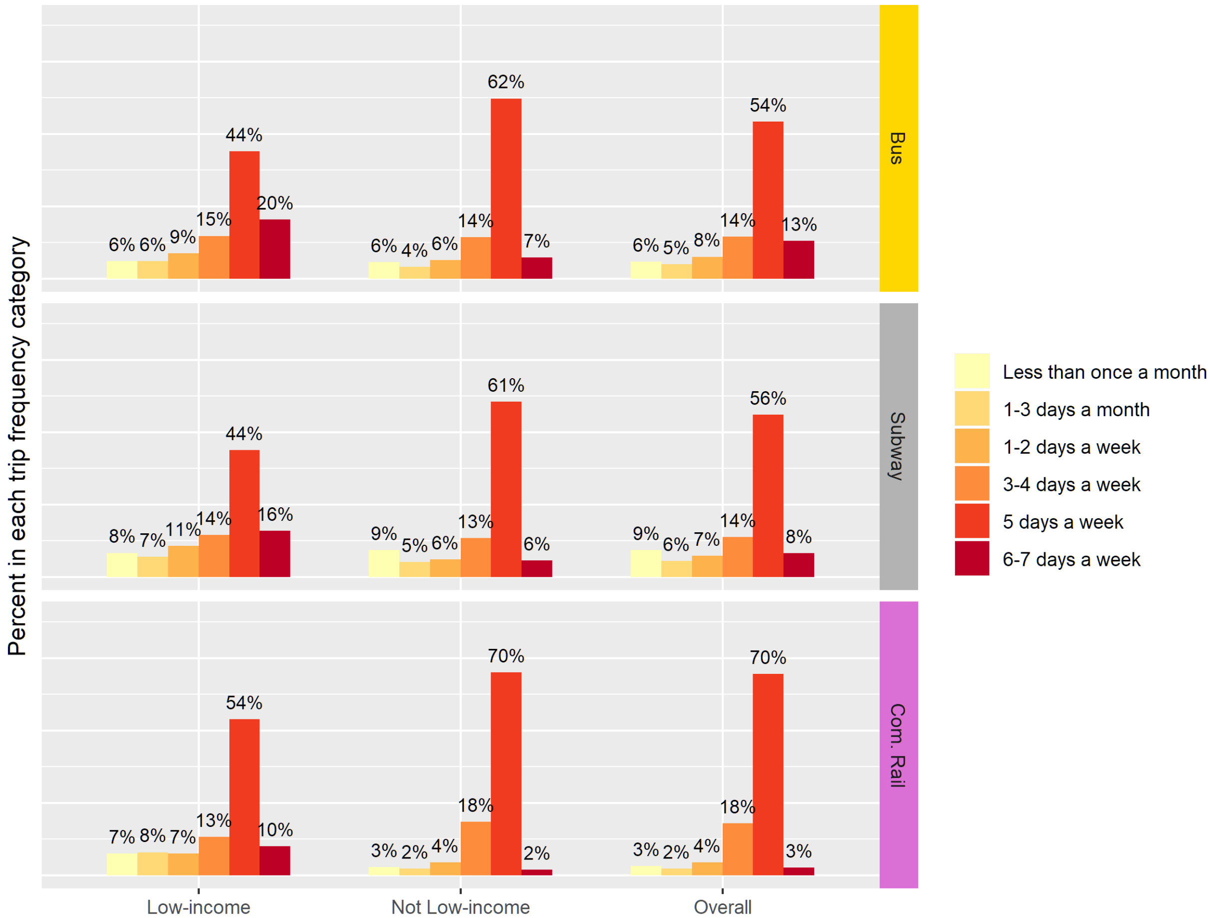


Source: MBTA 2015-2017 Ridership Survey.

Trip frequency. The passenger survey included a question about how frequently the current trip is made, "I make this trip on the MBTA ..." with a multiple choice set of possible responses. The results are presented in Figure 4-3. The distribution of responses for bus and subway are similar. There is a noticeable difference when segmenting by income. The percent responding "5 days a week" is about one-third lower for low-income individuals compared with others, while the percent responding "6-7 days a week" is three time higher for low-income individuals. This could be explained in a few different ways: (1) low-income riders are more likely to take non-work related trips because they are less likely to own a car, and/or (2) low-income riders are more likely to have multiple part-time jobs that require travel on more than five days.

A note of caution regarding these results. The question did not ask "how frequently do you ride the MBTA," but instead asked for the frequency of the current trip being described in the response. The former, though, is more relevant to understanding baseline trip generation rate.

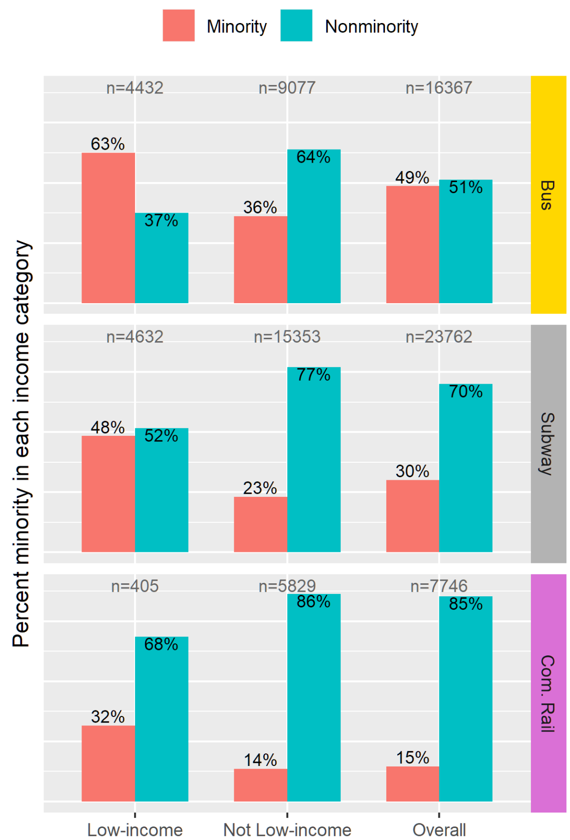
Figure 4-3 Number of trips based on income and mode



Source: MBTA 2015-2017 Ridership Survey.

Minority status. Figure 4-4 shows ridership by minority status. Overall, there is minimal disparity on buses but a significant disparity by subway and commuter rail. But the results are interesting when broken down by income status. A higher percent of bus riders with lower incomes are minorities but the ratio is about even for subway riders. And the ratio is reversed for commuter rail riders, meaning low-income commuter rail riders are predominantly non-minority.

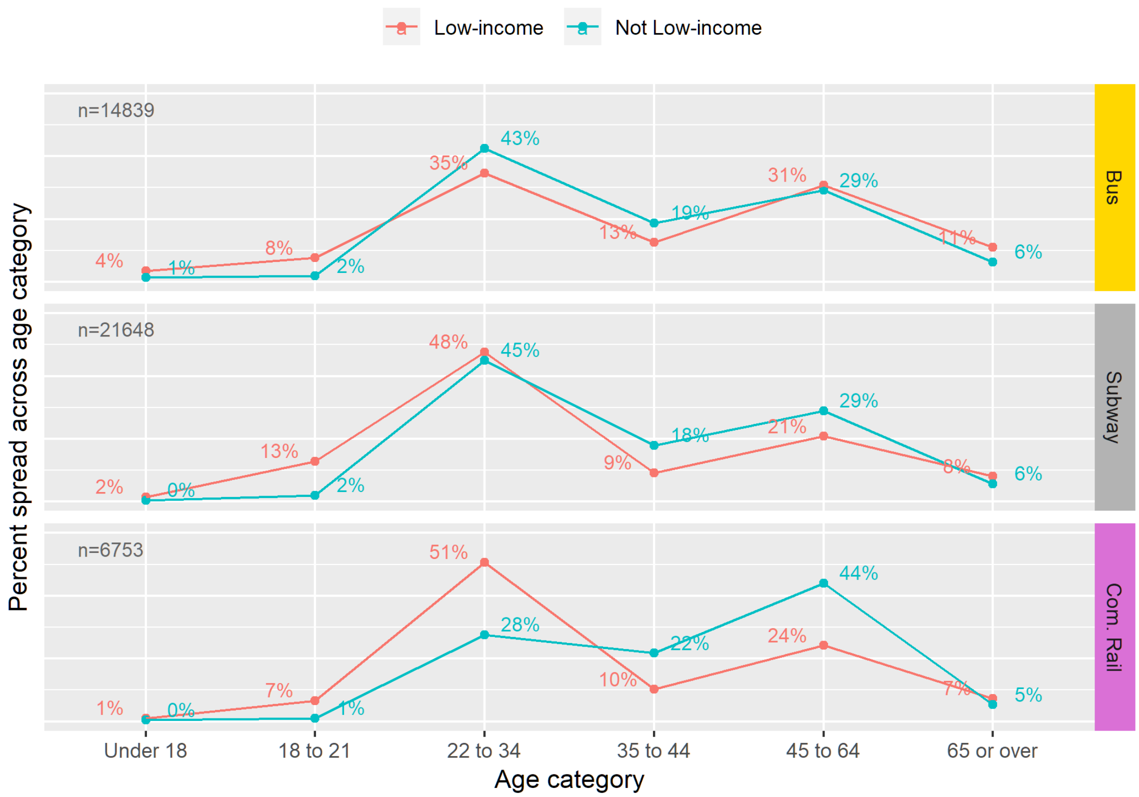
Figure 4-4 Distribution of MBTA riders by income, minority status, and mode



Source: MBTA 2015-2017 Ridership Survey.

Age. Figure 4-5 shows how ridership is distributed over age categories by income status. The red line represents low-income riders compared with the blue line representing other riders. For each income category, the percent of riders for each mode in each age category are indicated. Adding the values horizontally for each income category will result in 100%. The distribution of riders across age category is similar for bus and subway. Overall, most riders are between 22-34 and 45-64.

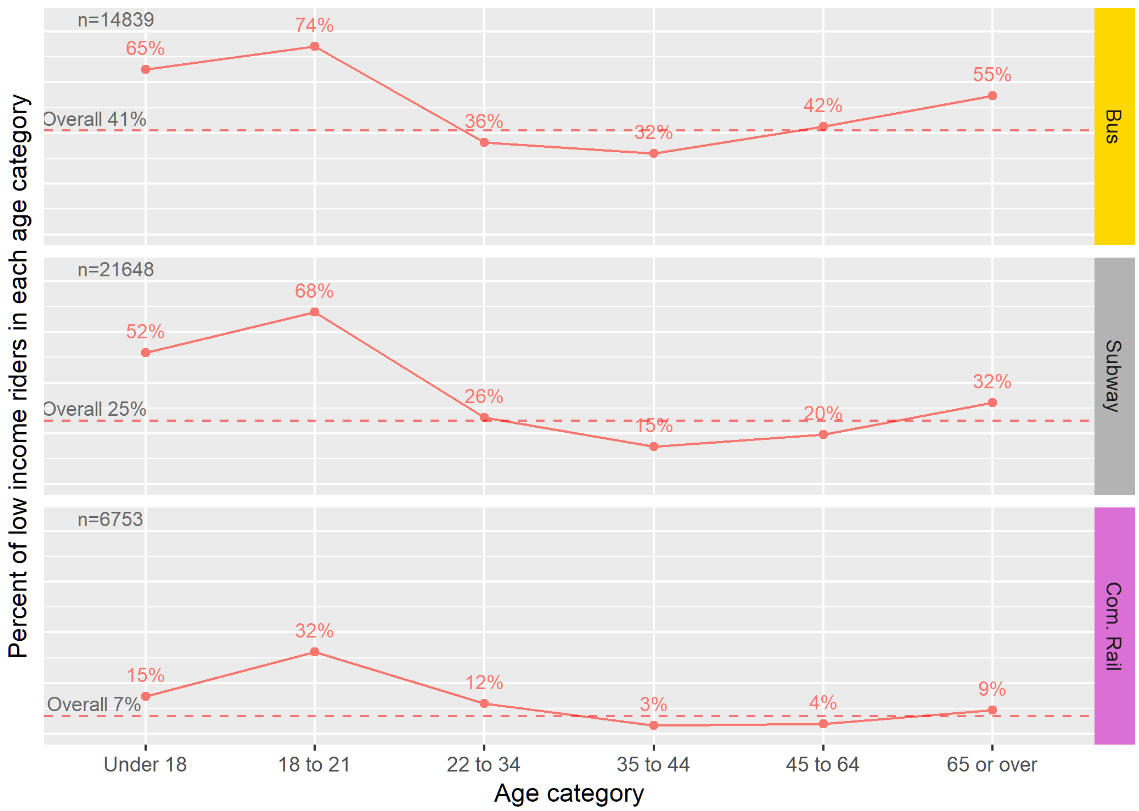
Figure 4-5 Distribution of income status across age category



Source: MBTA 2015-2017 Ridership Survey.

Figure 4-6 presents the data differently, showing the percent low-income for each age category. Younger riders and those over age 65 have a higher percentage of low-income riders. For example, 74% of bus riders and 68% of subway riders are between the ages of 18 and 21 are low-income. This supports the value of the recently implemented "Youth Pass" program (Paget-Seekins et al., 2015).

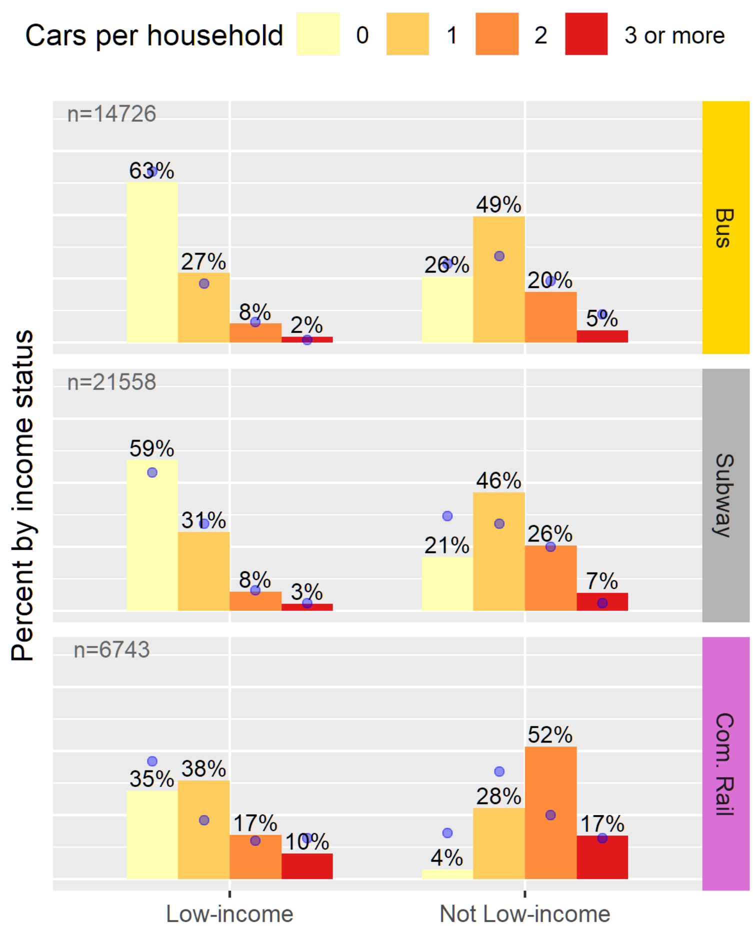
Figure 4-6 Income status in each age group



Source: MBTA 2015-2017 Ridership Survey.

Vehicle ownership. Vehicle ownership is an important indicator of transit-dependent ridership. Figure 4-7 shows the breakdown of household car ownership by income status. The breakdown for bus and subway is similar. These are in line with the national average values indicated by blue dots. About 60% of low-income individuals who ride the bus or subway do not own cars.

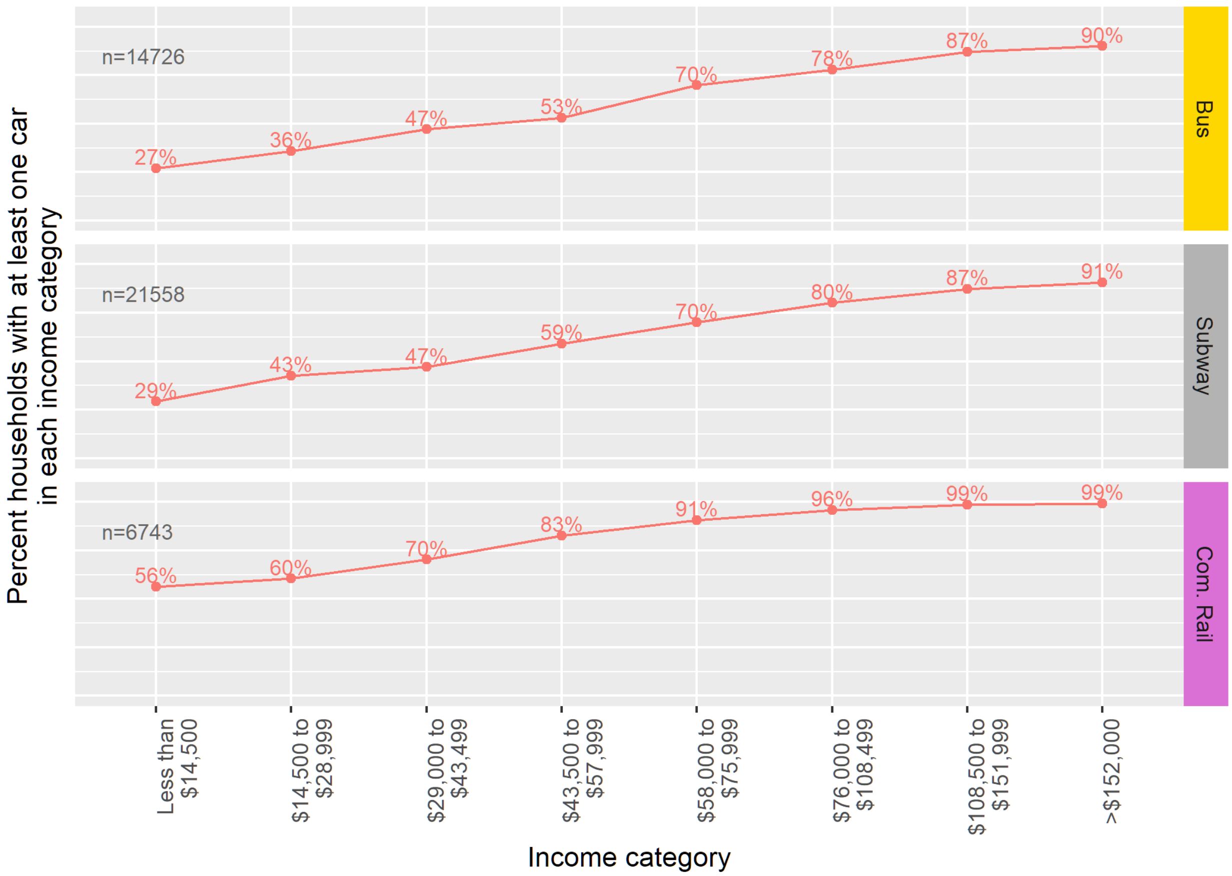
Figure 4-7 Car ownership by income status



Source: MBTA 2015-2017 Ridership Survey.

Figure 4-8 provides a more granular analysis of car ownership by household income. The value shown on the plot is the percent of households in each income category owning at least one car. Not surprisingly, less than 30% of bus and subway riders with incomes of less than $15,000 own a car, and percent car ownership increases with income category.

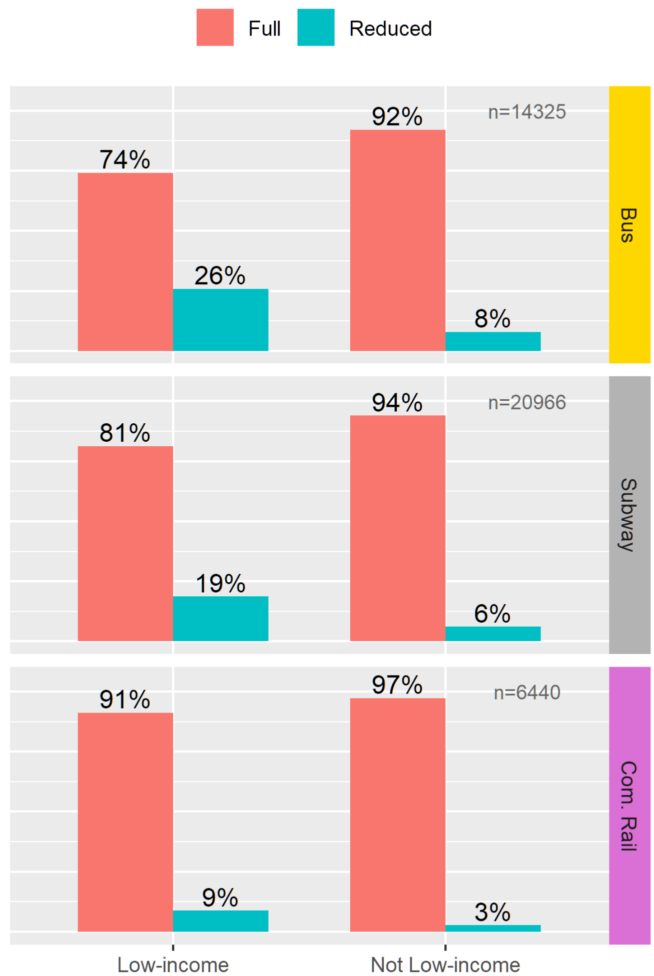
Figure 4-8 Car ownership by income category



Source: MBTA 2015-2017 Ridership Survey.

Reduced fare. Figure 4-9 shows the percent paying full and reduced fares by income category. A quarter of all low-income bus riders pay with an existing discount card (e.g., Senior, Disability, or Student) while 75% pay the full fare. This ratio is smaller for low-income subway riders of whom 20% pay with existing discount cards. The implication is that three quarters of those who would potentially meet the low-income threshold currently do not receive any discount.

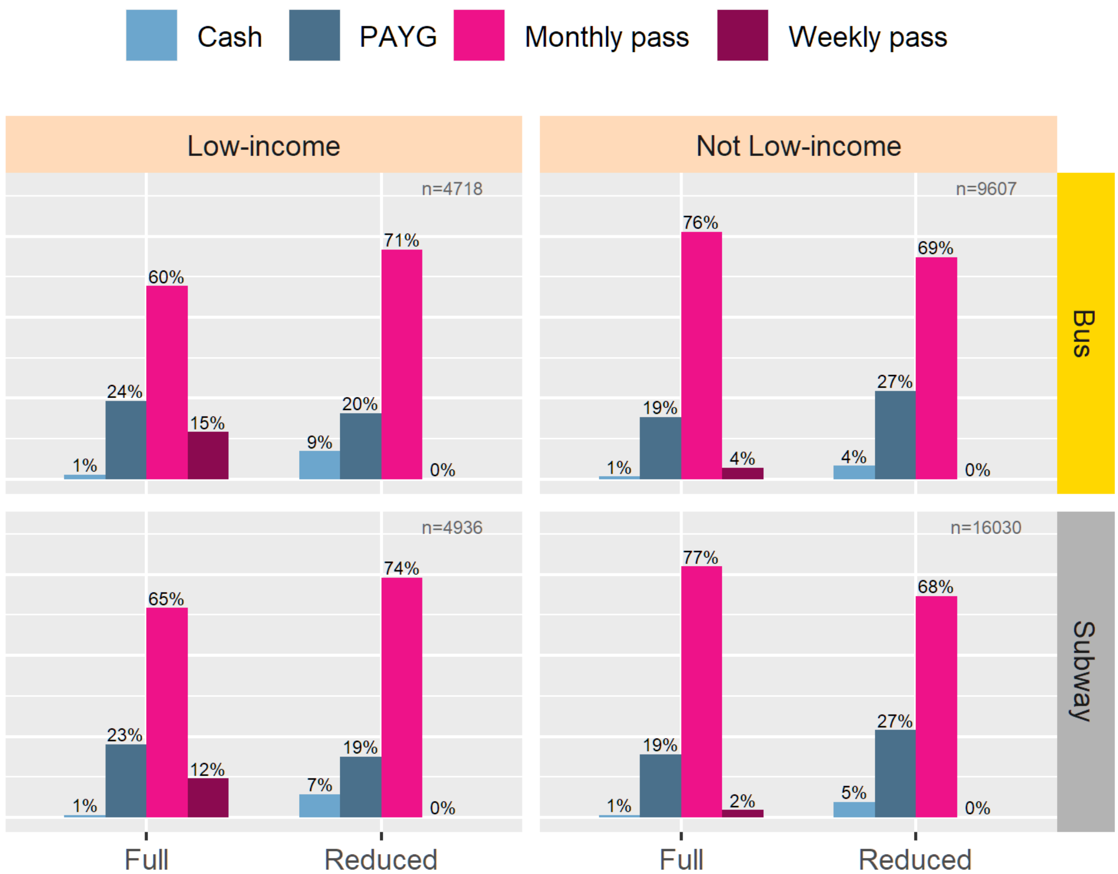
Figure 4-9 Percent paying full or reduced fare by income status



Source: MBTA 2015-2017 Ridership Survey.

Figure 4-10 shows the distribution of how people pay for transit. The primary methods are paying cash on board buses, pay per ride (PAYG) using a smart card, monthly pass, or weekly pass. There should not be any cash payments on the subway, so individuals might have reported paying cash when they really used cash to purchase a single-ride ticket at the vending machine. The majority surveyed paid for their fare with a monthly pass. Low-income individuals paid for weekly passes at about 5 times the rate of those earning more, about 15% compared with 3%. This aligns with the notion that those with limited means will choose to purchase weekly passes because of the smaller cash outlay required.

Figure 4-10 Payment method by income status and mode



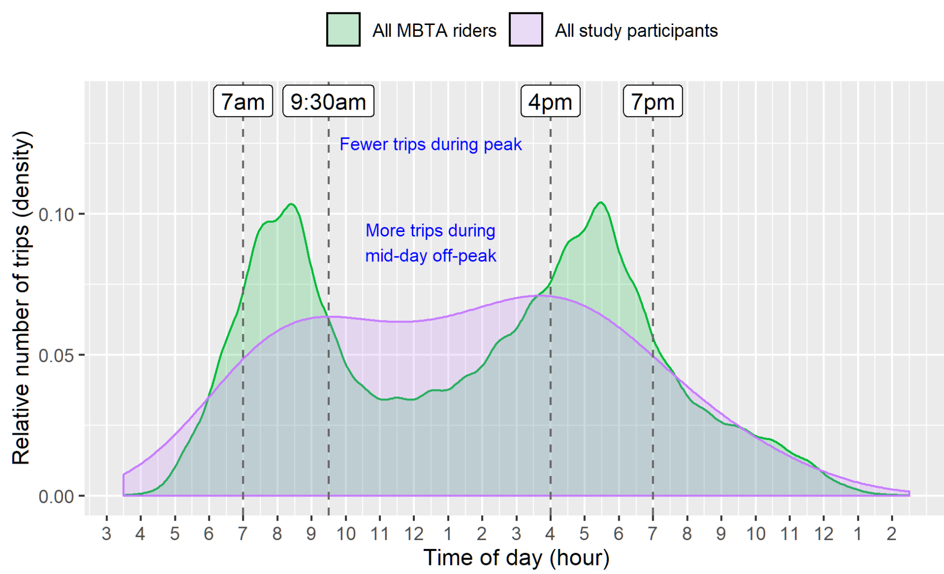
Source: MBTA 2015-2017 Ridership Survey.

4.2 MBTA smart card comparison

The smart card dataset generated by the low-income participants in the study can be used to compare travel behavior along several dimensions between low-income riders and the overall MBTA ridership.

The first dimension is time-of-day travel. The MBTA and other US transit authorities have expressed concerns that a low-income fare discount might induce additional ridership during the weekday peak hours which already experience crowding. Figure 4-11 shows the fraction of trips per hour throughout the day. The low-income participants in the study took a higher fraction of off-peak trips than the average MBTA user (shown in green), notably so in the middle of the day.

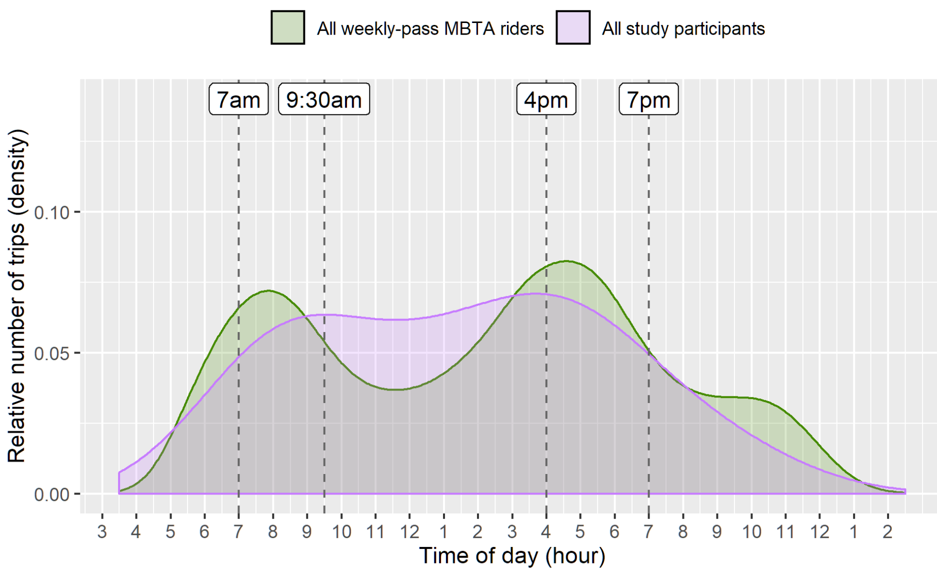
Figure 4-11 Time of day transit usage comparison between study participants (purple) and overall MBTA ridership (green)



Note: Data for the month of March 2019 was used to represent the average across the MBTA bus and subway system.

The participant dataset can also be used to evaluate the potential use of existing MBTA data as a proxy for low-income. Referring back to Figure 4-10, the MBTA travel survey reported low-income individuals are 5 times more likely to purchase a weekly pass. About 15% of low-income individuals choose a weekly pass compared with 3% of others. This suggests that overall MBTA weekly pass smart card usage data might serve as a proxy for low-income riders. Figure 4-12 compares the time of day trip distribution of the low-income individuals in the study (purple) and all weekly pass users (orange). The two datasets shown in Figure 4-12 match more closely than those in Figure 4-11. One problem with the data is that weekly pass users, while consisting mostly of low-income riders, are not likely to be representative of all low-income riders because only 15% of low-income riders pay with a weekly pass. This is an area worth further study.

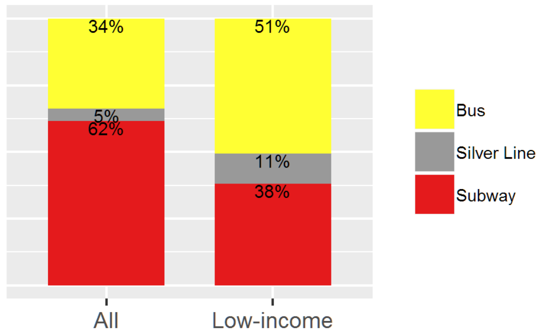
Figure 4-12 Time of day transit usage comparison between all study participants combined (purple) and only MBTA riders paying with a weekly pass (green)



Note: Data for the entire month of March 2019 was used to represent average transit usage by time of day across the MBTA bus and subway system.

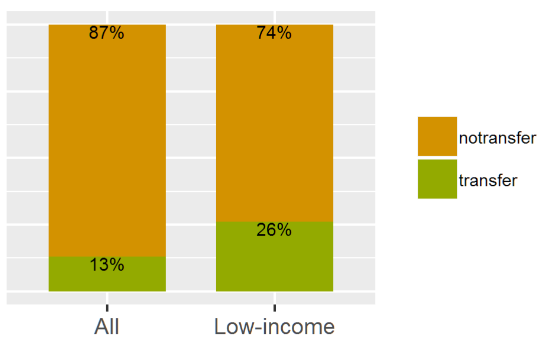
Smart card usage data for the participants in the study was used to determine the percent of trips taken on different modes, and this was compared with mode use of all riders on the MBTA subway and bus system for March 2019 (Figure 4-13). Based on an analysis of smart card data from the automated fare collection system, participants in the study relied on bus service (which includes the Silver Line) for 60% of their trips, while 40% of all MBTA trips included a subway leg. MBTA passenger survey data presented in a previous section provides different results, indicating that 43% of all low-income riders use the bus compared with 33% of all MBTA trips. This discrepancy is worthy of further investigation.

Figure 4-13 Comparison of mode usage between study participants (Low-income) and all MBTA riders (All).



A similar analysis was conducted comparing the number of trips that required a transfer for the participants in the study and MBTA riders overall (Figure 4-14). Low-income riders take twice as many trips (26%) requiring transfers than the average rider.

Figure 4-14 Comparison of transfers between study participants and all MBTA riders



4.3 PUMS census microdata

In 2012, the Dukakis Center at Northeastern University released a report *Staying on Track* that found commute time disparities by race for greater Boston (Pollack, 2012). One of the key findings is that African Americans in greater Boston spend 66 hours more hours per year commuting by bus than whites, 34 more hours per year by subway and 12 more hours per year by car (Figure 4-15).[15] The study gained media attention with the headline, "Black commuters face longer trips to work; Disparity particularly bad on buses, averaging 80 minutes more per week" (Moskowitz, 2012). The "64 hours" number has subsequently been used regularly by organizations wanting to highlight racial inequities with respect to transportation (McFarland, 2019).

Figure 4-15 Commute time disparity by race (Pollack, 2012)

Note: while the data is from Northeastern University, the figure was created by the Boston Globe (Moskowitz, 2012)

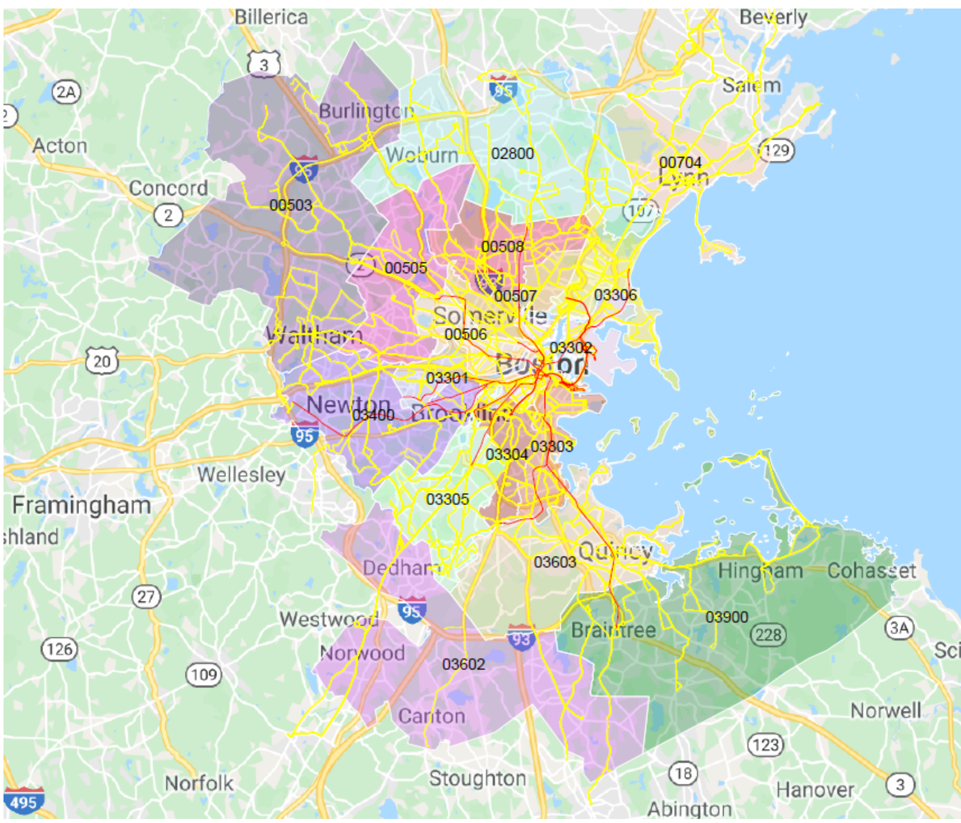
The analysis requires the use of American Community Survey (ACS) Public Use Microdata Sample (PUMS) data because cross-tabulations of commute time, race, mode, and income are not available through pre-tabulated (or summary) ACS data products. PUMS files include a sample of responses to the actual ACS including variables for nearly every question asked. There are two types of files, one for *Person* records and one for *Housing Unit* records. Each record in the *Person* file represents a single person who are organized into households. To ensure privacy, variables in the PUMS files have been modified. For instance, particularly high incomes are replaced with a top-code value and uncommon birthplace or ancestry responses are grouped into broader categories. The geographic detail is

[15] Using PUMS data for the 5-year period 2005-2009, they calculated the average difference in one way commute times by race and transportation mode and then converted that difference into hours per year of by assuming ten commutes per week and fifty commuting weeks per year. They did not indicate which PUMS areas they included in their analysis.

also limited, with about five PUMS areas defined in the inner core Boston area. A PUMS file for an individual year contains data on approximately 1% of the population (approximately 100,000 people are represented in one PUMS area) and those covering a five-year period contain data on approximately 5% of the population. By nature of the number of The datasets are incredibly large and therefore challenging.

For the analysis, I included PUMS geographic areas the include the bulk of the urban Boston bus and rapid transit network (see Figure 4-16). The PUMS 2012-2016 5-year data sample was used.[16]

Figure 4-16 PUMS areas included in the analysis (red lines represent rapid transit lines and bright yellow lines represent bus routes)



The results are shown in Figures 4-20 to 4-19. The commute time disparity for African

[16] The analysis was conducted in R using Anthony Damico's `lodown` package to download the PUMS dataset and store it `RSQLite` format (see http://asdfree.com/american-community-survey-acs.html). The `survey` package was used for the analysis.

Figure 4-17 Bus trips: Commute time disparity by race controlling for income

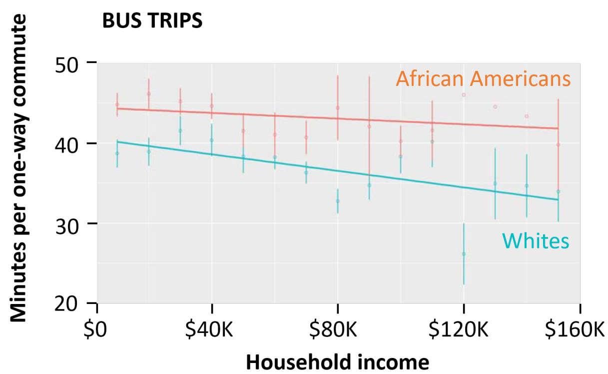


Figure 4-18 Transit trips: Commute time disparity by race controlling for income

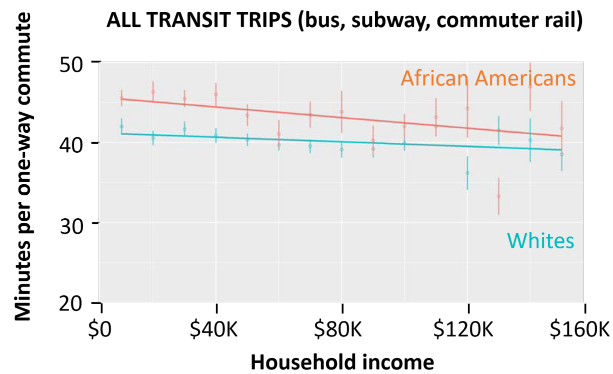


Figure 4-19 Car trips: Commute time disparity by race controlling for income

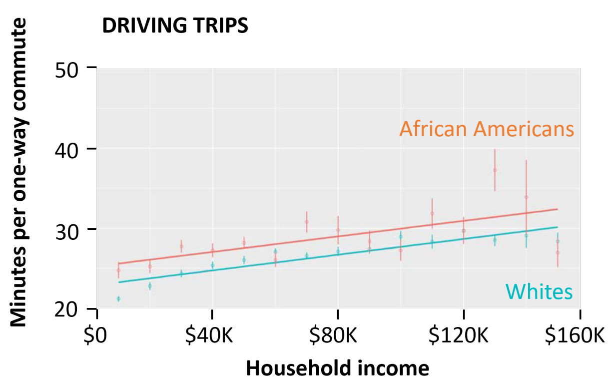
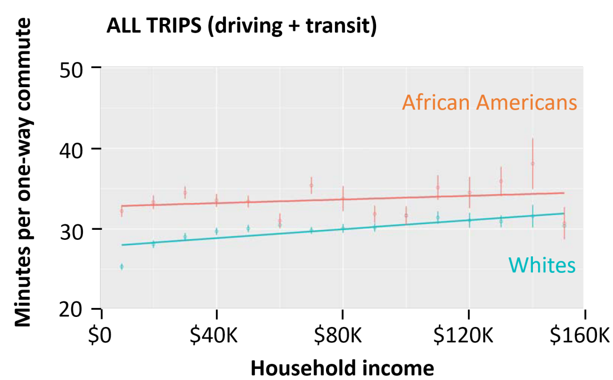


Figure 4-20 All trips: Commute time disparity by race controlling for income



American bus riders ranges from four minutes per one-way commute (33 hours/year) for the lowest income group to eight minutes for the highest income group (66 hours/year). Likewise, for all transit trips combined (including bus, subway, and commuter rail), the disparity ranges from 4 minutes per day to 2 minutes per day. There is also a disparity of about 3 minutes per one-way commute trip for driving trips regardless of income. For all modes combined, there is a disparity of $3-5$ minutes per one-way trip.

There are interesting conclusions regarding the correlation between commute time, income, and race. As people become more wealthy, their bus commute time decreases, but declines faster for whites. One explanation is that the quality of bus service is better in wealthier neighborhoods. Another potential explanation is that higher-income individuals have a lower tolerance for bus commute time and therefore more often opt for driving. Driving commute times lengthen with income supporting the theory that wealthier individuals trade off longer commute times against housing and school quality.

An unfortunate conclusion drawn from this analysis is that race is correlated to average commute time even when correcting for income. This is a troubling finding that supports the theory that racism is embedded into the physical and institutional structures of society in ways that we often do not recognize.

5

Response to discounted fares

In presenting the quantitative findings from the randomized controlled evaluation, this chapter addresses the second research question: *What is the causal effect of a fare subsidy on the number of trips taken by low-income riders?* Using smart card data, average treatment effects are calculated for the number of transit trips taken overall and segmented by mode (bus or subway). Data from the ChatBot daily travel diary are used to calculate the average treatment effects on different trip purposes. Because of the large number of zeros in the dependent count variable for trip types, a zero-inflated negative binomial regression analysis was used.

5.1 Treatment effect on the overall number of transit trips taken

The treatment effect is defined as the difference between the average weekly number of trips taken by participants in the treatment group and the average taken by the control group. The number of linked trips for each participant is obtained from smart card usage data. A linked trip represents a full journey that could consist of several bus and/or subway legs.

MBTA pre-processes the smart card data to determine multi-stage trips such that transfers are considered part of the same trip (Gordon et al., 2013). This is necessary for a transit system like the MBTA where there is only *tap-in* and not *tap-out*.

Participants in the control group took on average 8.5 trips per week while those in the treatment group took on average 10.8 trips per week (Table 5.1 and Figure 5-1). This indicates a treatment effect of 2.3 trips per week (a 27% difference). The elasticity of demand, calculated by dividing the percent change in usage by the percent change in price (Equation 5.1), is -0.54.

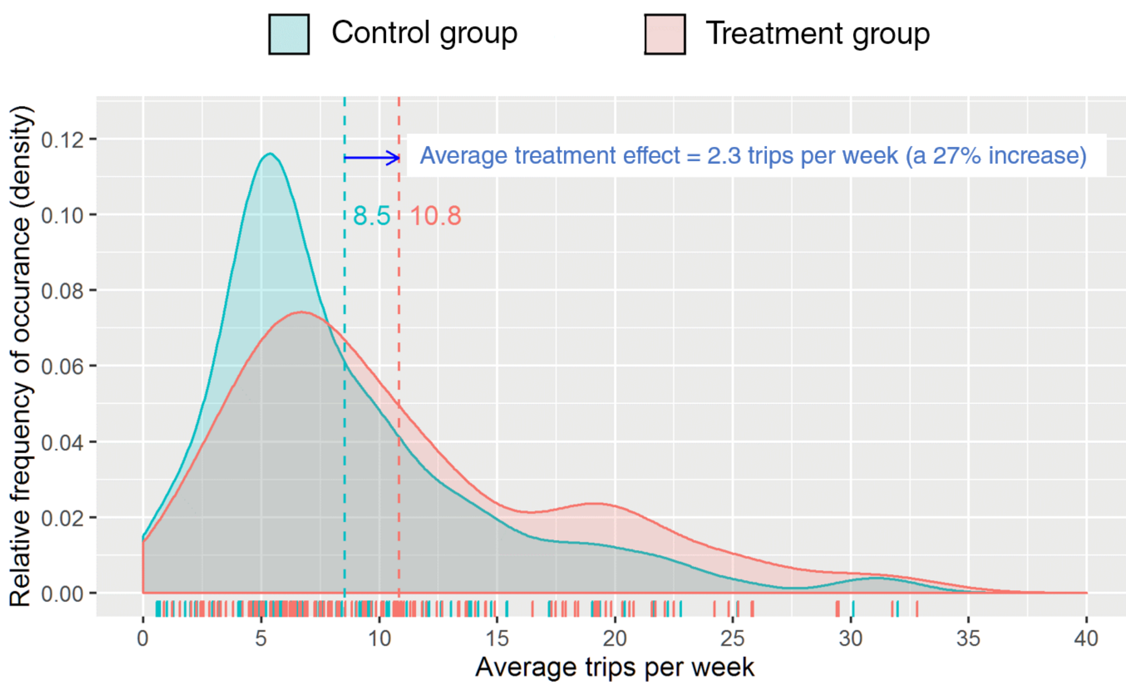
$$\text{Elasticity} = \frac{\%\,\Delta Q}{\%\,\Delta P} = \frac{\%\,\Delta\text{trips}}{\%\,\Delta\text{price}} = \frac{+0.27}{-0.50} = -0.54 \tag{5.1}$$

A Welch's 2-group t-test was used to test the statistical difference in means of the two groups. The 95% confidence interval of the difference is 0.5 to 4 trips per week with the likely true difference lying somewhere between those extremes. The lower bound of the confidence interval is quite close to zero suggesting that the treatment effect could be small. A larger sample size would have provided for a narrower confidence interval.

Table 5.1 Two-sample t-test for equal means

		Control			**Treat**		**95% Confidence Interval**		
	mean	**sd**	**n**	**mean**	**sd**	**n**	**of the difference**	***df***	**t**
Trips per week	8.51	6.49	121	10.78	7.70	121	0.47, 4.07	235.6	2.48**
							or 2.3 ± 1.8		
							Note: *p<0.1; **p<0.05; ***p<0.01		

Figure 5-1 Treatment effect on average number of trips by group



5.2 Treatment effect on the number of transit trips taken, segmented by mode

The difference in number of trips taken by the treatment and control groups segmented by mode is presented in Table 5.2. A single trip may include a combination of subway and bus legs. Trips were categorized as (1) including a subway leg, or (2) including only bus legs. Figure 5-2 shows the distribution of trips that included only bus legs and Figure 5-3 shows the distribution of trips that include a subway leg. Additional bus trips contributed a larger magnitude (+1.8) to the overall increase in number of trips taken (+2.3) than additional subway trips, which only contributed +0.5 (the +0.5 value is not statistically significant, so could be zero or as high as 1.5.) These equate to a 38% increase in number of bus trips and a 13% increase in number of subway trips over their respective control group means. These results suggest that receiving the discount had a much larger effect on bus trips than subway trips.

Table 5.2 Two-sample t-test for equal means, segmented by mode

		Control			Treat		95% Confidence Interval		
Trips per week...	mean	sd	n	mean	sd	n	of the difference	*df*	t
...that include subway leg	3.8	4.0	121	4.3	4.0	121	0.5 ± 1.0	235.6	0.941
...that only include buses	4.7	4.4	121	6.5	5.9	121	1.8 ± 1.3	235.6	3.07***
							Note: *p<0.1; **p<0.05; ***p<0.01		

Figure 5-2 Average bus-only trips per week

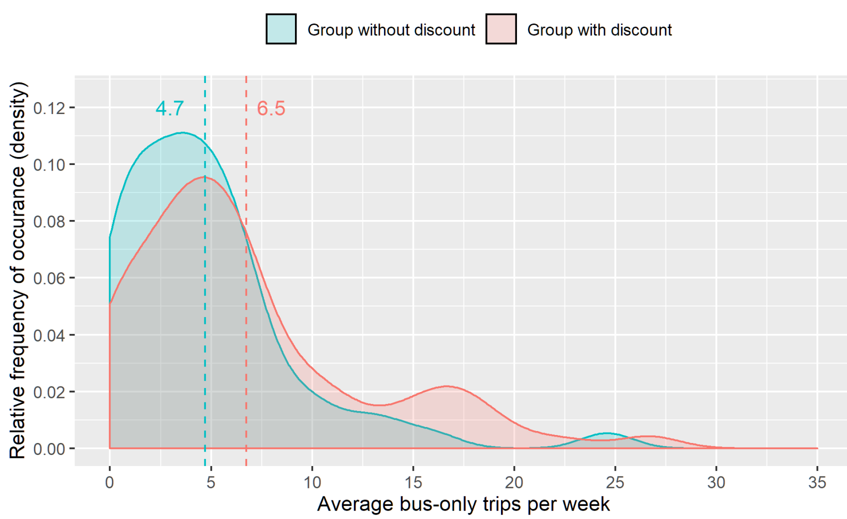
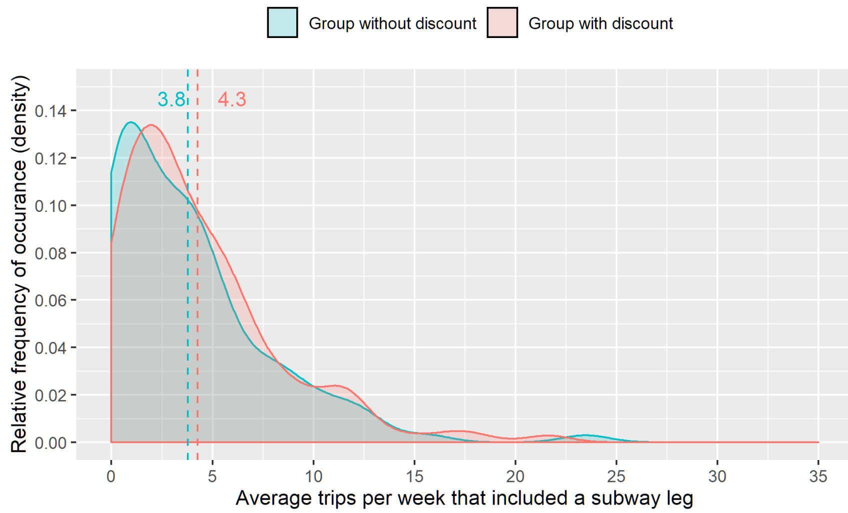


Figure 5-3 Average trips per week that included a subway leg



5.3 Treatment effect on trip purposes

This section presents results from the ChatBot trip diary. Each travel diary entry collected by the ChatBot over the duration of the study was subsequently hand coded into the categories listed in Table 5.3. If more than one purpose was listed in a single daily diary entry, multiple codes were used. Some coding examples from different participants are shown in Table 5.4. About 5% of the ChatBot responses were unable to be coded, usually because detail of the trip purpose was not included in the response. This did not introduce bias into the analysis because the control and treatment groups both had the same percent of uncodeable responses.

The coded values were then tallied by trip type providing the total number of each trip type reported. Because participants did not provide a diary entry for each day, these totals were normalized by the number of days for which a user reported a response. This produces trip generation rates for each trip purpose, presented as trips per month. The assumption was made that trips are generated at the same rate for the missing days as they were for the

Table 5.3 Coding abbreviations

Abbreviation	Description
wrk	Work related
fam	Visiting family and friends
kid	Taking care of a child (e.g., daycare, school)
recr	Recreational
shop	Shopping and errands
educ	School, training, job search
health	Healthcare

Table 5.4 Sample diary entries and coding

Diary_response	Codes
Went to doctor at Boston Medical. Went to work. Came home.	health,wrk
Work and pickup my son from after school	wrk,kid
Train to Braintree visit grandkids	fam
Buenas tardes, estuve en el mercado	shop
To see mom and doctors appointment and back home	fam,health

reported days (note that a participant responding "none," if no transit trips were taken that day, counts as a response).

5.3.1 Summary statistics

Summary statistics of the results by trip type is presented in Tables 5.5 and 5.6. The data contains a large fraction of zeros for participants who did not report any trips of a particular trip type as presented in Table 5.5. In preparation for introducing the zero-inflated mixture model in the next section, Table 5.6 provides summary statistics on the data with all zeros removed. The top of Figure 5-5 provides a visual display of the trip generation rates for the two study arms with the zeros not included in the box-plot. The lower plots present the average treatment effect and the 95% confidence interval for each trip type. The analysis was conducted both on the full dataset including the zeros and on the dataset with the zeros removed. These findings suggest that there is a statistically significant average treatment effect on the number of healthcare related trips taken by participants. There is also some evidence suggesting that participants receiving the discount took more trips to visit family and friends. Figure 5-5 uses a density plot to illustrate the distributions by group.

Table 5.5 Summary Statistics: all data included

All

Statistic	wrk	fam	kid	recr	shop	educ	health
n	242	242	242	242	242	242	242
min	0	0	0	0	0	0	0
max	30	26	23	23	36	16	26
mean	5.95	1.57	2.33	2.26	4.04	2.06	4.13
sd	8.20	2.90	4.85	3.70	4.95	3.80	4.49
frac zeros	0.51	0.63	0.69	0.56	0.29	0.64	0.30

Treatment Group

Statistic	wrk	fam	kid	recr	shop	educ	health
n	127	127	127	127	127	127	127
min	0	0	0	0	0	0	0
max	30	26	23	23	36	16	26
mean	6.04	2.21	2.55	2.50	4.61	2.04	5.10
sd	8.35	3.49	5.34	4.05	5.94	4.07	5.32
frac zeros	0.50	0.52	0.69	0.51	0.25	0.69	0.24

Control Group

Statistic	wrk	fam	kid	recr	shop	educ	health
n	115	115	115	115	115	115	115
min	0	0	0	0	0	0	0
max	29	7	21	14	14	16	13
mean	5.84	0.85	2.09	1.99	3.40	2.08	3.06
sd	8.07	1.84	4.26	3.28	3.48	3.50	3.03
frac zeros	0.52	0.76	0.70	0.61	0.33	0.60	0.36

Table 5.6 Summary Statistics: zeros excluded

All

Statistic	wrk	fam	kid	recr	shop	educ	health
n	118	89	74	107	172	86	170
min	1	1	1	1	1	1	1
max	30	26	23	23	36	16	26
mean	12.19	4.26	7.62	5.10	5.68	5.79	5.88
sd	7.86	3.39	6.08	4.07	5.02	4.37	4.29
frac zeros	0	0	0	0	0	0	0

Treatment Group

Statistic	wrk	fam	kid	recr	shop	educ	health
n	63	61	39	62	95	40	96
min	1	1	1	1	1	1	1
max	30	26	23	23	36	16	26
mean	12.17	4.61	8.31	5.11	6.17	6.47	6.75
sd	8.12	3.79	6.75	4.50	6.13	4.90	5.12
frac zeros	0	0	0	0	0	0	0

Control Group

Statistic	wrk	fam	kid	recr	shop	educ	health
n	55	28	35	45	77	46	74
min	1	1	1	1	1	1	1
max	29	7	21	14	14	16	13
mean	12.22	3.50	6.86	5.09	5.08	5.20	4.76
sd	7.62	2.15	5.22	3.43	3.09	3.80	2.48
frac zeros	0	0	0	0	0	0	0

Figure 5-4 Density plots illustrating the relative distribution of the average number of trips by purpose for each participant

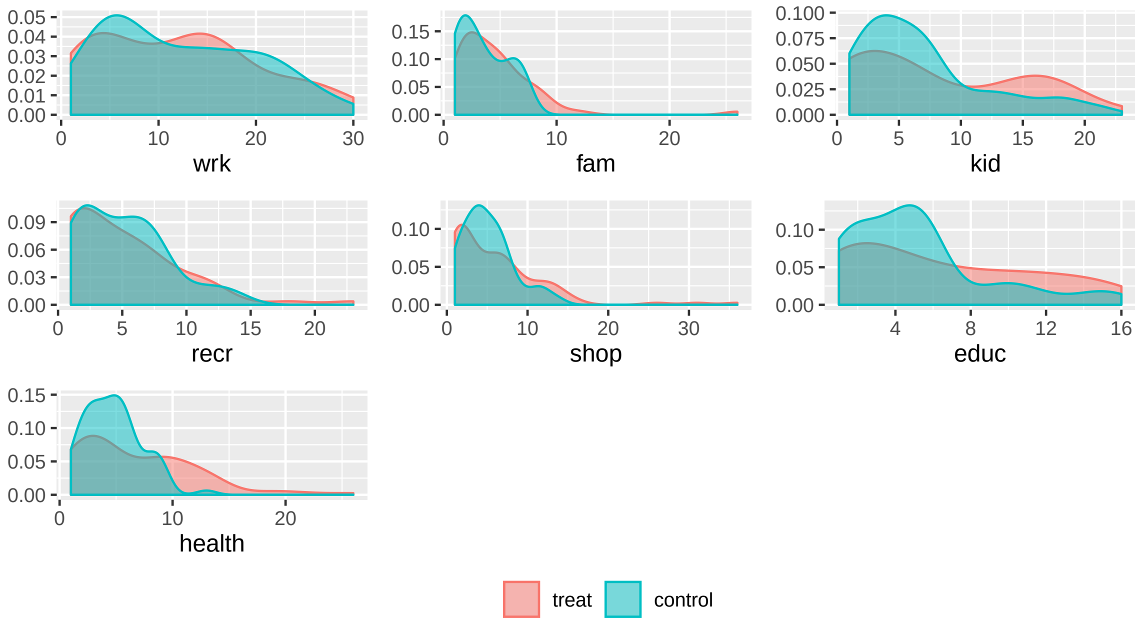


Figure 5-5 Distribution of number of trips for each trip purpose for the treatment and control groups

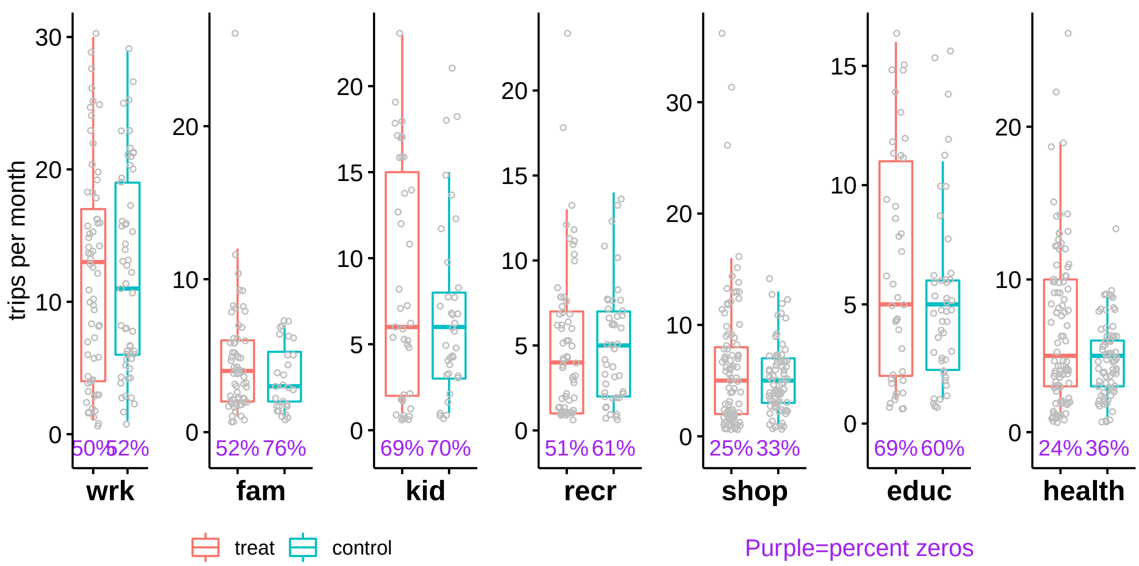
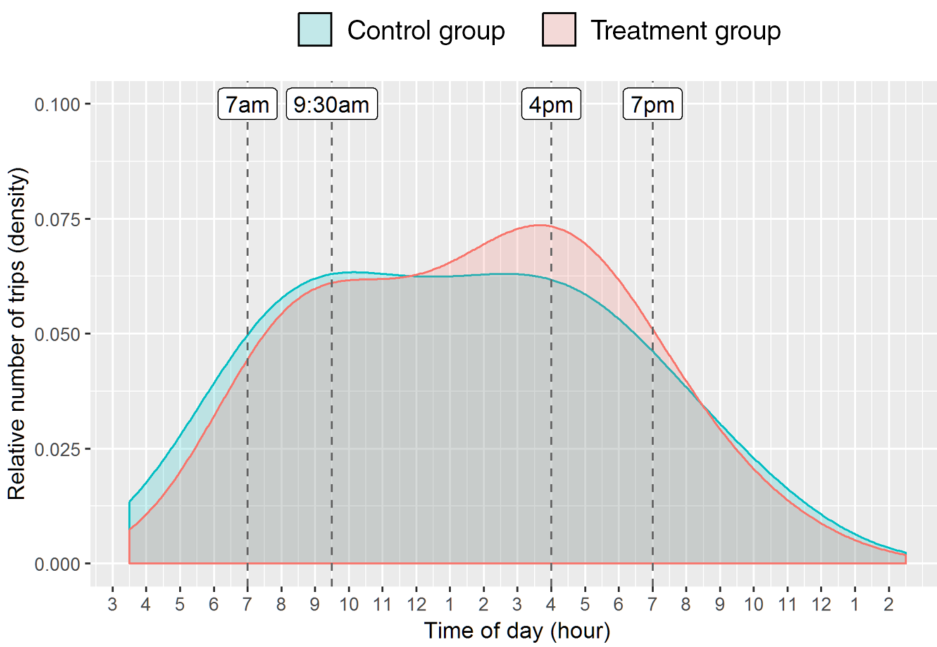


Figure 5-6 indicates that the two groups in the study show a similar pattern though there appears to be some evidence that participants receiving a discount did take a slightly higher fraction of their trips in the afternoon leading up to the PM peak.

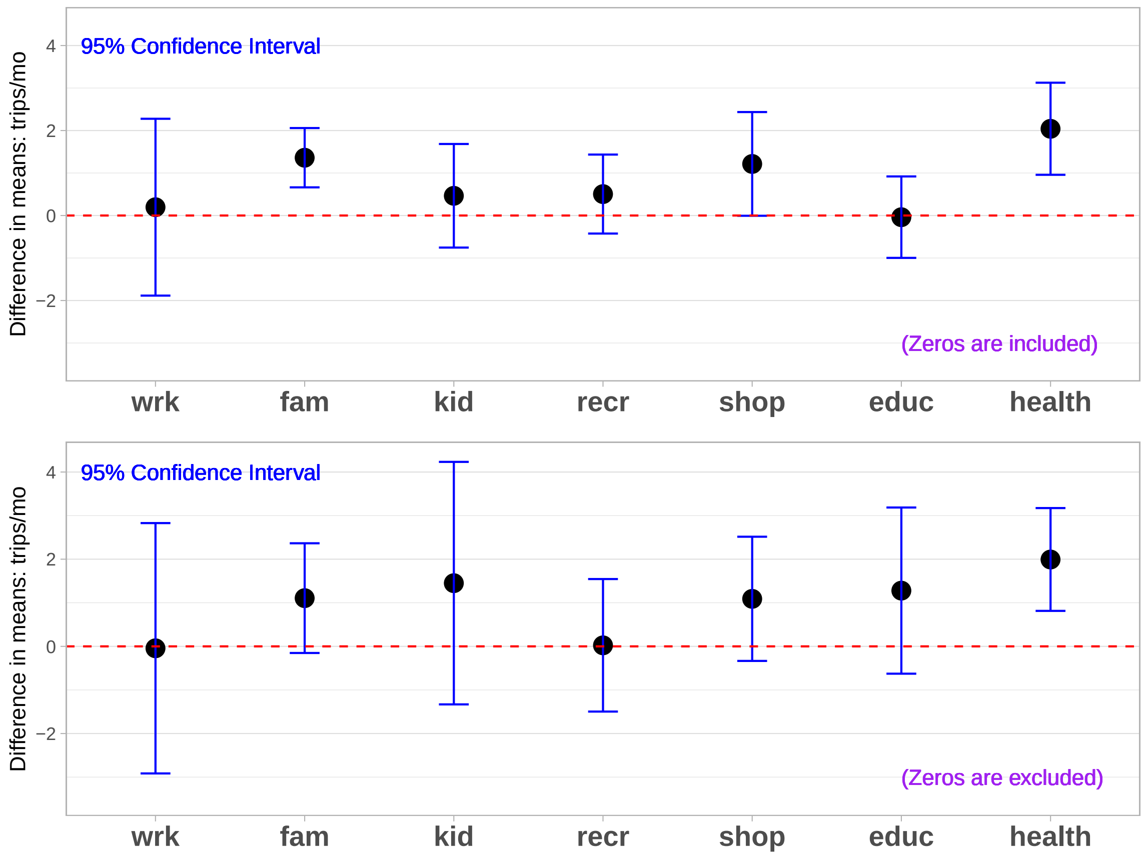
Figure 5-6 Time of day transit usage comparison between treatment and control groups



5.3.2 Treatment effect

To test for the equivalence of means of the two groups, I used a Welch's 2-sample t-test. Figure 5-7 presents the difference in means between the treatment and control groups. A 95% confidence interval is included for each value.

Figure 5-7 Treatment effect on the average number of trips taken by trip purpose



5.3.3 Zero-inflated regression

A regression model was developed to further investigate the treatment effect. Because of the large number of zeros in the count data for number of trips taken in different categories, a zero-inflated negative binomial regression model was developed. This approach is often taken when the response variable exhibits over-dispersion (the conditional variance is greater than the conditional mean) and/or an excess number of zeros. Most count data sets exhibit such behavior, many quite significantly. Zero-inflated mixture models are commonly used to handle such situations. The theoretical foundation of such models is the assumption that there are two mechanisms involved. The first influences a binary outcome of "some" or "none." If "some," then a second mechanism influences "how much."[17]

The results are presented in two parts, shown in Table 5.7. The top is the negative binomial component where the dependent variable is the number of trips per month taken for each trip type. The bottom is the zero-inflated component where the dependent variable is a dummy where 1 indicates zero trips were taken. Trips to visit family and friends and trips to healthcare are the only two trip types that have statistically significant results. For example, looking at family trips (fam), receiving the treatment decreases the odds of having no family trips (-1.03^{***}), and is correlated to an increase in the number of family trips taken (0.33^{*}). The treatment has no effect on whether zero trips are taken (-0.47) but does have an effect on the number of healthcare trips taken (0.39^{***}). The result regarding healthcare trips is discussed in more detail in the next chapter.

The magnitudes of the results are trickier to interpret. The incident risk ratio for the negative binomial model and odds ratio for the logistic (zero inflated) model, calculated by exponentiating the coefficients, are presented in Table 5.8. For example, looking at visits to family and friends (fam), the effect of receiving the treatment on the odds of being in the group with zero trips is a factor of 0.357. This is equivalent to about a third of the chance. Stated conversely, someone is three times more likely to have a positive number of family trips if they receive the discount.

The magnitude of the treatment effect for the count model component results is shown in the upper portion of Table 5.7. The baseline number of family trips is 3.0 per month among those who have a chance of not being in the zero group. Receiving the treatment correlates to 1.4 times the number of trips (equivalent to a 50% increase or about 1.5 trips per month).

In sum, receiving a discounted transit fare increases the chances of having at least one family trip by a factor of three, and those in the non-zero group who receive a transit discount

[17] A Vuong test indicated that a zero-inflated negative binomial model provides a better fit than a zero-inflated Poisson model for each of the trip purpose types.

take 50% more trips.

Table 5.7 Zero-inflated negative binomial model

	Negative binomimal component						
	wrk	fam	kid	recr	shop	educ	health
treat	−0.004	0.33*	0.22	0.01	0.23	0.25	0.39***
	(0.14)	(0.20)	(0.24)	(0.20)	(0.15)	(0.20)	(0.12)
Constant	2.49***	1.11***	1.80***	1.45***	1.47***	1.52***	1.48***
	(0.10)	(0.17)	(0.18)	(0.17)	(0.12)	(0.15)	(0.10)

	Zero-inflated component						
	wrk	fam	kid	recr	shop	educ	health
treat	−0.07	−1.03***	0.03	−0.46	−0.40	0.45	−0.47
	(0.26)	(0.31)	(0.30)	(0.32)	(0.46)	(0.29)	(0.34)
Constant	0.05	0.94***	0.64***	0.14	−1.27***	0.19	−0.84***
	(0.19)	(0.24)	(0.23)	(0.26)	(0.36)	(0.23)	(0.24)
Observations	242	242	242	242	242	242	242
Log Likelihood	-568	-354	-368	-435	-598	-384	-590
Note:					*p<0.1; **p<0.05; ***p<0.01		

Table 5.8 Zero-inflated negative binomial model exponentiated coefficients

Coefficient	wrk	fam	kid	recr	shop	educ	health
Count model: (Intercept)	12.017	3.024	6.038	4.276	4.351	4.583	4.381
Count model: treat=TRUE	0.996	1.397	1.244	1.006	1.259	1.290	1.478
Zero model: (Intercept)	1.056	2.549	1.893	1.147	0.280	1.205	0.431
Zero model: treat=TRUE	0.930	0.357	1.026	0.630	0.668	1.576	0.625

5.3.4 Zero-inflated regression including demographics

The zero-inflated regression model is now expanded to include demographic covariates obtained from each participant during the on-boarding process. Those variables are described in Table 5.9. The negative binomial component results are presented in Table 5.10 and the zero-inflated component results are presented in Table 5.11. Adding demographic covariates does not change the core findings described in the last subsection, but does provide some additional insights into trip making behavior. Looking at the zero-inflated component, though the results indicate that the treatment has a statistically significant effect on reducing the chances of having no shopping trips, the large magnitude, when exponentiated, results in a value very close to zero suggesting these results are meaningless. There are some additional findings regarding the demographic variables. For example, blacks and Hispanics have higher odds of having reported at least one educational or training trip. Single parents have higher odds of reporting a trip involving a child while lower odds of reporting recreational trips. Being older is also correlated with a decreased odds of having any child-related trips. All of these findings are intuitive.

Turning attention to the negative binomial component of the model, older individuals take fewer educational and training trips. Being black or Hispanic positively correlates with more recreational trips. Finally, single parenthood correlates with 0.6 ($e^{-0.45}$) fewer shopping trips per month. While there are plausible explanations for these findings, there is no basis for them in existing literature.

Table 5.9 Model covariates

Covariate	Type	Description
Treat	Dummy	T if in the treatment group; F if in the control group
Gender	Dummy	female or male
Age	Continuous	Age
Race	Categorical	Black, Hispanic, or white
Singleparent	Dummy	T if a single parent with dependents; F if not
Workstatus	Dummy	T if employed either full-time or part-time; F if unemployed

Table 5.10 Negative binomial component of the regression model

	Negative binomimal component						
	wrk	fam	kid	recr	shop	educ	health
treat	-0.03	0.40^{*}	0.35	-0.04	0.25	0.32	0.41^{***}
	(0.14)	(0.23)	(0.28)	(0.20)	(0.16)	(0.22)	(0.13)
genderfemale	-0.14	-0.09	-0.47	-0.35	0.12	0.09	0.02
	(0.17)	(0.24)	(0.50)	(0.22)	(0.20)	(0.23)	(0.16)
age2	-0.001	0.002	-0.02	0.01	0.001	-0.02^{**}	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
raceblack	0.25	-0.25	-0.07	0.61^{**}	0.15	0.34	0.005
	(0.18)	(0.22)	(0.31)	(0.28)	(0.20)	(0.32)	(0.15)
racehispanic	-0.08	-0.06	0.03	0.73^{**}	0.26	0.52	0.02
	(0.23)	(0.31)	(0.40)	(0.36)	(0.24)	(0.35)	(0.19)
raceother	0.19	0.13	-0.44	0.32	0.30	0.24	-0.26
	(0.23)	(0.30)	(0.52)	(0.32)	(0.26)	(0.39)	(0.22)
singleparent	-0.09	0.09	0.01	-0.23	-0.45^{**}	-0.08	-0.16
	(0.16)	(0.19)	(0.43)	(0.22)	(0.18)	(0.22)	(0.13)
workstatus	0.04	0.03	0.05	-0.12	-0.19	-0.18	-0.18
	(0.14)	(0.20)	(0.25)	(0.19)	(0.16)	(0.20)	(0.12)
Constant	2.53^{***}	1.07^{**}	3.01^{***}	0.91^{*}	1.41^{***}	2.07^{***}	1.30^{***}
	(0.36)	(0.53)	(1.02)	(0.47)	(0.44)	(0.52)	(0.38)
Observations	242	242	242	242	242	242	242
Log Likelihood	-554	-350	-332	-422	-571	-373	-576
Note:					*p<0.1; **p<0.05; ***p<0.01		

Table 5.11 Zero-inflated component of the regression model

	Zero-inflated component						
	wrk	fam	kid	recr	shop	educ	health
treat	-0.22	-1.08^{***}	0.22	-0.54	-45.70^{*}	0.45	-0.37
	(0.28)	(0.33)	(0.42)	(0.34)	(26.88)	(0.32)	(0.38)
genderfemale	0.37	0.15	-0.28	0.31	-3.58	0.92^{**}	-0.61
	(0.36)	(0.39)	(0.53)	(0.41)	(6.28)	(0.40)	(0.43)
age2	0.03^{**}	0.03^{*}	0.07^{***}	-0.004	-8.06^{*}	-0.01	-0.04^{**}
	(0.01)	(0.01)	(0.02)	(0.02)	(4.75)	(0.01)	(0.02)
raceblack	-0.06	0.36	0.70	0.06	4.17	-0.88^{**}	-0.16
	(0.35)	(0.39)	(0.52)	(0.47)	(3.84)	(0.43)	(0.45)
racehispanic	-0.35	0.16	0.36	0.87	-17.32	-1.50^{***}	-0.52
	(0.46)	(0.50)	(0.66)	(0.56)	(292.57)	(0.52)	(0.67)
raceother	-0.47	0.10	-0.01	-0.01	8.09	-0.83	0.43
	(0.47)	(0.50)	(0.83)	(0.59)	(323.61)	(0.54)	(0.54)
singleparent	-0.23	-0.31	-2.99^{***}	0.73^{**}	-65.06	-0.18	-0.83^{**}
	(0.31)	(0.34)	(0.59)	(0.36)	(325.04)	(0.34)	(0.40)
workstatus	-1.07^{***}	-0.21	-0.39	-0.22	6.42	-0.07	0.40
	(0.28)	(0.31)	(0.38)	(0.33)	(5.35)	(0.31)	(0.37)
Constant	-0.38	-0.16	-0.01	-0.34	249.77^{*}	0.74	1.43
	(0.72)	(0.82)	(1.08)	(0.85)	(147.29)	(0.80)	(0.98)
Observations	242	242	242	242	242	242	242
Log Likelihood	-554	-350	-332	-422	-571	-373	-576
Note:							*p<0.1; **p<0.05; ***p<0.01

6

Access to healthcare

This chapter focuses on access to one particular destination type, namely healthcare. Results from the randomized controlled evaluation in section 5.3 indicate that providing a 50% discounted transit fare to low-income riders in Boston increases travel by an average of 2.3 transit trips per week on average. Based on the trip purposes reported by participants through the daily travel diary collected by the ChatBot, discounted fares account for an additional two trips per month to healthcare appointments. Two areas are investigated in further detail. The first section explores the hypothesis that there are different mechanisms regarding behavior (a) whether or not any healthcare trips were reported, and (b) the number of healthcare trips reported per month. A zero-inflated negative-binomial regression is used to determine whether the treatment, demographic, and/or self-reported health variables correlate to zero healthcare trips. The second section relies on interview data to establish that healthcare visits for chronic illnesses are being skipped because of transit fare cost. The interviews revealed no evidence that medical care for acute illnesses or emergencies are affected.

6.1 Background

Improving the health of low-income individuals is an important policy objective, especially because income correlates highly with health risk factors such as higher rates of heart disease, stroke, diabetes, obesity, hypertension, or physical limitation (Center for Health Statistics, 2012). At the same time, low-income individuals frequently do not seek necessary medical care, which leads to poorer health outcomes and increased costs (NCHS, 2017). A significant body of research has been devoted to pinpointing the causes of such behavior in order to suggest ways to ameliorate the problem. The conclusions are that reasons for avoiding medical care are nuanced, highly variable, and include both structural barriers (e.g., cost of care, transportation access, or time constraints) and personal factors (e.g., the perceived need for care or attitudes toward medical institutions) (Taber, Leyva, & Persoskie, 2015). With expanded healthcare insurance coverage from the Affordable Care Act and MassHealth reducing one of the major structural barriers, cost, attention has shifted to secondary barriers such as lack of transportation. For example, MassHealth provides a free transportation service called *Prescription for Transportation* (PT1) which provides privately contracted paratransit ride services when ordered by a physician. Although technically only available to those who cannot use public transit to access the appointment, this is not well enforced (See Appendix E for more details). Another example is Harvard Pilgrim Healthcare's program launched in January 2020 which offers 12 to 24 free rides each year (depending on location) for non-emergency medical transportation to Medicare Advantage members.[18]

The siloing of disciplines has led to discounting the public health implications of planning decisions. Recognizing this, planners and public health officials have recently come together

[18] "Transportation Program Reduces Barriers to Healthcare Access," December 12, 2019, *Managed Healthcare Executive*. https://www.managedhealthcareexecutive.com/news/transportation-program-reduces-barriers-healthcare-access

to address what are referred to as *social determinants of health*. Going beyond a focus on biomedical causes of disease and chronic health problems, new research points to education, economic stability, community safety, and availability of adequate housing and healthful food as causal factors in poor health outcomes for marginalized populations. One of the social determinants that has not received much attention is transportation.

Much of the health and transportation literature, as well as public policy itself, focuses on *active transportation* connecting the built environment to health outcomes, far less attention is given to transportation barriers to healthcare accessibility. Studies indicate that neighborhood walkability encourages exercise (Handy, Boarnet, Ewing, & Killingsworth, 2002), and public transit use correlates with an increase in walking (Lachapelle, Frank, Saelens, Sallis, & Conway, 2011). A similar disconnect between transportation and health outcomes exists in the policy realm as well. For example, the 2009 Massachusetts transportation reform legislation established the *Healthy Transportation Compact* to leverage an inter-agency collaboration to increase levels of bicycling and walking through *complete streets* infrastructure, improve mobility of persons with disabilities, and apply Health Impact Assessments to transportation projects (Arcaya, 2014). The legislation does not address improving health outcomes through better transportation access to healthcare for low-income populations (MGL, 2009).[19]

Lack of transportation, though, is frequently cited in the health literature as a barrier to health-care access. A review of that literature indicates the lack of adequate public transit as one of the causes, an implicit assumption being that individual cities that do have robust transit systems should not have transportation issues. The following are the two most comprehensive reviews of existing literature. These two reviews, and relevant cited research,

[19] The stated mission, though, invites a broader interpretation: "adopt best practices to increase efficiency to achieve positive health outcomes through the coordination of land use, transportation and public health policy."

are augmented by additional material from my own literature search.

- Hughes-Cromwick, Wallace, Mull, & Bologna (2005) review 200 sources focusing on access to healthcare by populations considered *transportation disadvantaged.*
- Syed, Gerber, & Sharp (2013) review 61 peer-reviewed studies on transportation barriers to healthcare access from a systematic literature search.

A commonly referenced statistic is that in a given year, about 3.6 million Americans do not obtain non-emergency medical care resulting from a lack of transportation (R. Wallace, Hughes-Cromwick, Mull, & Khasnabis, 2005). This study relied primarily on the National Health Interview Survey (NHIS) ($n = 90,000$), conducted by the National Center for Health Statistics and the Medical Expenditure Panel Survey ($n = 30,000$, a subset of the first survey) conducted by the Agency for Healthcare Research and Quality. It suggested that household incomes below $20,000 per year and being non-white were more highly associated with missed healthcare trips because of lack of transportation. About 80% (weighted) of those citing transportation barriers in the study live in urban areas. Also using the NHIS, other researchers found that transportation access and travel time issues were nearly as important a barrier as the cost of healthcare itself for those with incomes less than 200 percent of the poverty level (O'Malley & Mandelblatt, 2003).

Most of the studies presented in Syed's synthesis described transportation barriers in general and somewhat vague terms, such as "difficulty finding transportation," "lack of transportation," "no transportation," or "transportation assistance needed" thereby providing limited details as to the root causes (Syed et al., 2013). One study identified reasons for missed appointments: forgot (27%), transportation problems (21%), and time off of work (14%) (Samuels et al., 2015). More specifically, travel time has been identified as a barrier. In a study ($n = 51,500$) of low income individuals in Pittsburgh, Wallace found that longer travel times strongly correlated with an increased number of missed pediatric visits. This correlation holds for patients taking transit or driving (D. J. Wallace et al., 2018). In another study, low-income adults in Atlanta who did not drive to healthcare appointments had higher incidences of delayed care and not having a regular source of care (Rask, Williams, Parker, & McNagny, 1994). Overall, Syed's findings collectively suggest that lack or inaccessibility of transportation might be associated with less health-care utilization, lack of regular medical care, and missed appointments (Syed et al., 2013).

While published literature documents the existence of unmet transportation needs for healthcare access, there is limited understanding of access and affordability issues in urban areas where a robust transit system exists. Even more limited are studies of transit barriers specifically, and where transit barriers are identified, affordability is not differentiated from other transit access barriers. Lack of car ownership is commonly cited as a critical factor. Certainly in places with limited transit availability, the lack of car ownership for low-income individuals would be expected to limit access to healthcare. While this is germane to much of the US, it is not a forgone conclusion that car ownership affects poorer residents in urban areas with robust transit access.

The biggest gap in the literature is addressing differences in transportation barriers for individuals living in transit-rich urban areas where it is viable to access healthcare appointments without a car, and urban areas where that is not the case. Even in urban Boston, there are areas poorly served by transit. Most studies define *urban* broadly such that it is not possible to tease out the role of transit.[20] Very few of the studies in Syed's review pertained specifically to an urban transit-rich setting and none specifically addressed affordability (Syed et al., 2013).

A few studies focusing on transit and healthcare do exist. One study found that a transit strike in Minneapolis resulted in increased frequency of missed nurse visits suggesting, unsur-

[20] Urban areas in research studies are often defined as *metropolitan statistical areas* (MSAs).

prisingly, that many who rely on transit have limited alternatives (Pheley, 1999). Another found that those relying on public transit missed pediatric appointments more frequently than those with a car. In that study, 86% of patients riding public transportation ($n = 51$) to get to medical appointments reported missing an appointment because of transportation compared to 27% of those arriving by car ($n = 22$) (Sipe et al., 2004).[21] Asthma patients in Philadelphia relying on public transit were less likely to follow-up with a primary care visit following emergency room visits for acute asthma episodes (Baren et al., 2001). Neither of the the latter two studies corrected for income as a potentially confounding factor.

6.2 Correlates of healthcare trips

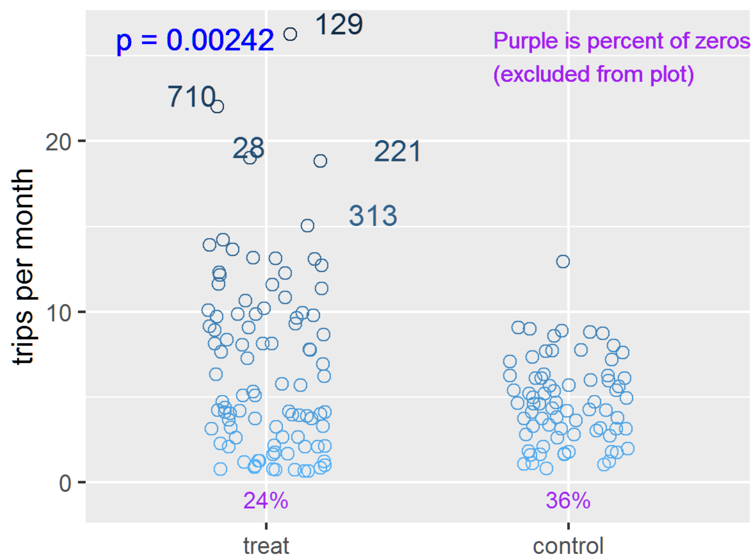
The randomized controlled evaluation study concluded that the treatment group, on average, took more healthcare trips than the control group. A curious finding is that 36% of the treatment group reported zero healthcare trips while that number was only 24% for the control group (See Figure 6-1.) This suggests a counter-intuitive finding that an individual receiving the treatment has an increased likelihood of taking zero healthcare trips. To investigate this finding in more detail, regression analysis was employed. Other demographic covariates are included in the model. A second question is whether there is any correlation between an individual's self-reported health and the number of healthcare trips reported. That covariate is also included in the model.

6.2.1 Self-reported health indicators

In addition to the demographic variables collected during the on-boarding process, a measure of self-reported health was also collected. Self-reported health status is often used in epidemiological research as a proxy for a person's overall well-being in terms of social, bi-

[21] The study was not peer reviewed, the sample size was small, and the area studied is not revealed.

Figure 6-1 Distribution of healthcare trips by study arm

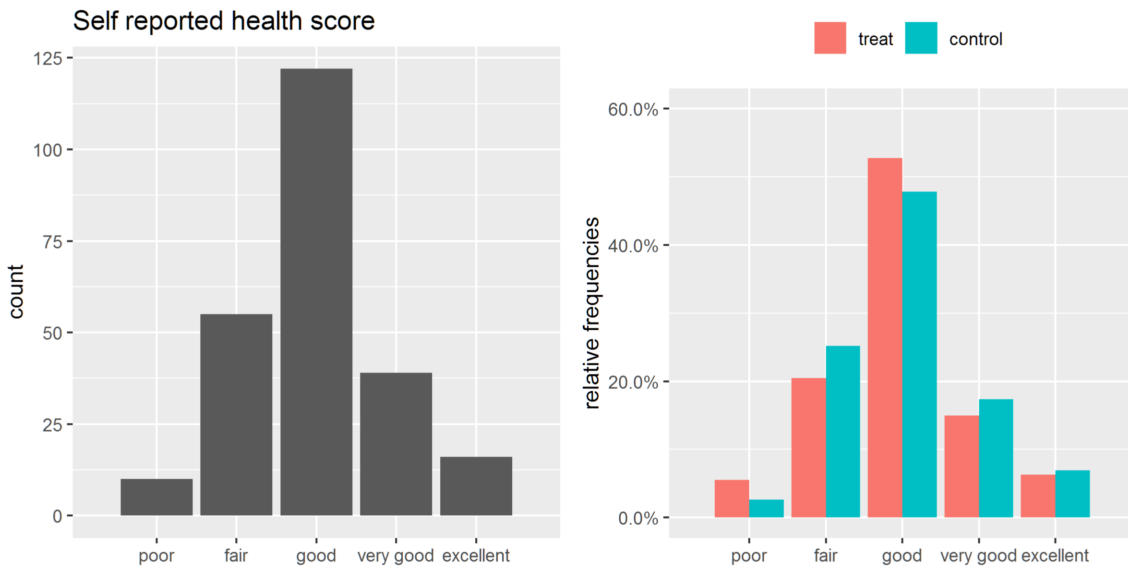


ological and psychological health. Its use has been growing in popularity in social science research. A single-item measure of self-reported health (on a 5-point Likert scale) is often used. It is derived from the RAND Corporation's 36-Item Short Form Survey Instrument (SF-36), a very popular instrument in medical research for evaluating health-related quality of life based on a conceptual model developed in the 1980s (Anita Stewart et al., 1992). This measure is commonly used as a proxy for general health because of its strong association with morbidity and mortality in diverse populations (DeSalvo, Bloser, Reynolds, He, & Muntner, 2006; Finch, Hummer, Reindl, & Vega, 2002; Idler & Benyamini, 1997). Following is the question used:

> *In general, would you say your health is:*
> *(1=poor, 2=fair, 3=good, 4=very good, or 5=excellent?)*

Figure 6-2 provides a summary histogram of the composite scores overall and by study group. About half the responses are *good*. There is a balance between treatment and control groups.

Figure 6-2 Distribution of self-reported health score



There are competing theories on how individual health status might predict healthcare utilization. It is plausible that healthy people are healthy because they obtain the regular care they require. On the other hand, those in poor health might obtain regular care because their condition requires it. Overall, though, one would expect that health would correlate with healthcare utilization. One study found that self-reported health was moderately good predictor of healthcare costs (Cunningham, 2017), though it did not specifically address utilization rates which would not be expected to correlate in the same fashion for individuals in good health compared with individuals in fair or poor health.

To simplify the regression analysis presented in the next section, a binary variable was created to represent the concept of being in *good* health or *bad* health. The other option would have been to use the ordered Likert scale as individual coefficients. Ordinal Likert scale data cannot be used as interval data for parametric analysis.[22] Figure 6-3 plots the

[22] Rensis Likert developed this scale in 1932 to measure individuals' attitudes, with respondents using an ordinal scale to rate the degree to which they agree or disagree with a statement. Frequently, Likert-scale data is treated as interval data, but there are concerns with this approach. The mathematical distance between responses is not measurable and is likely unequal. The differences between "always," "often," and "sometimes," for example, are not necessarily equal. Therefore,

self-reported health score against the number of total transit trips (left plot) from the smart card usage data and total healthcare trips (right plot) from the ChatBot trip purpose survey. There is not a visually observable correlation and the Spearman's nonparametric rank test ρ values do not indicate any correlation, minimizing concerns regarding the use of this indicator.

Figure 6-3 Self-reported health and healthcare trips per month

6.2.2 Regression model results

The results from the zero-inflated negative binomial mixture model for healthcare trips is presented in Figure 6-4. The negative binomial component is a continuous variable representing the magnitude of the healthcare trip count variable for cases with non-zero values. Here, positive coefficients indicate a correlation with taking more healthcare trips. The zero-inflated component is a binary variable representing whether an individual had zero or non-zero healthcare trips. In this case, positive coefficients indicate a correlation with an individual having zero healthcare trips while negative coefficients indicate a correlation with

descriptive statistics, such as means and standard deviations, and parametric statistical tests have unclear meanings when applied to Likert scale data (G. Sullivan & Artino, 2013).

individuals having at least one healthcare trip.

Figure 6-4 Zero-inflated negative binomial mixture model results for healthcare trips

	Negative binomimal component	*Zero-inflated component*
	health	health
	(7)	(7)
treat	0.43***	−0.49
	(0.12)	(0.36)
healthgood	−0.18	0.84**
	(0.12)	(0.42)
age2	0.01	−0.04**
	(0.01)	(0.02)
singleparent	−0.15	−1.10***
	(0.13)	(0.38)
Constant	1.31***	0.67
	(0.31)	(0.79)
Observations	242	242

Note: *p<0.1; **p<0.05; ***p<0.01

The regression results do not indicate a statistically significant correlation between self-reported health and either the zero-inflated or the negative binomial model components. This is an unexpected finding. I would have expected to see a correlation between being in good health and a higher likelihood of having zero healthcare trips. I also investigated the hypothesis that a combination of being in poor health and receiving the treatment is correlated with an increased number of healthcare trips. A regression including an interaction term involving self-reported health and treatment did not show a statistically significant result.

The regression indicates that receiving the transit discount correlates with an increase in healthcare trips taken but does not correlate with whether there are zero (or conversely non-zero) healthcare trips. Looking at the negative binomial component in the first column, receiving the treatment is the only variable that has a statistically significant correlation with an increased number of healthcare trips. On the other hand, looking at the zero inflated component, the treatment does not correlate with whether an individual has zero or non-zero healthcare trips. This result makes intuitive sense. It is unlikely that receiving a transit discount would induce someone to begin going to appointments. This also aligns with the hypothesis that it is chronic healthcare visits that are the ones forgone, as participants who indicated any healthcare visits at all would have already been engaged in regular maintenance visits at the start of the study. Additional support for this finding is provided by the qualitative data presented in the next section. None of the covariates are correlated with the number of healthcare trips taken, but several did correlate with zero healthcare trip-taking behavior. The treatment and control groups had balanced covariates which is confirmed by the regression for the *negative binomial* component. The *zero inflated* component of the regression indicates a correlation between positive self-reported health and zero healthcare trips (conversely, negative self-reported health correlates with taking at least one healthcare trip.) This finding makes sense in that those in good health are likely to only go for annual checkups which have a low probability of being detected during the two month study period. If the the study duration was one year, these visits would more likely be detected and therefore change the regression results.

The continuous variable *age* is positively correlated with having at least one healthcare trip. Participants in the study were between the ages of 24 and 64 such that children and the elderly are not included. This finding supports the generally accepted notion that older individuals in that range go to more healthcare visits.

The regression also indicates that single parents are statistically more likely to have reported at least one healthcare visit. Nothing in the literature, though, supports this finding. One hypothesis is that some healthcare trips were attributed to the participant when in fact they were for the participant's dependent. This could have occurred during the coding process when a participant responded with, for example, "went to a doctor's appointment" and did not clarify who the appointment was for. If this were the case, I would have expected being a single parent to correlate with the number of healthcare trips taken, which it does not. Healthy dependents require more frequent doctor visits than older healthy individuals, so this finding may be the result of a higher likelihood of detecting such a visit during the short two-month study period.

6.3 Chronic vs. acute healthcare visits

Not obtaining needed non-emergency medical care because of transportation barriers might differ based on whether the missed care was for preventive care (e.g., immunizations, screening programs, prenatal care), treatment for chronic problems, or acute illnesses (Hughes-Cromwick et al., 2005). Wallace identified conditions more prevalent for those who miss care, shown in Table 6.1 (R. Wallace et al., 2005). The list includes both chronic and acute conditions as well as preventive care. In urban areas, those citing transportation as a barrier had higher rates of diabetes, heart disease, and hypertension. There is likely a difference in how individuals prioritize acute healthcare needs compared with regular routine maintenance visits for chronic illnesses, but this issue has received minimal research focus. Research has also pointed to the lack of a perceived social support network as a cause of delaying needed medical care (Reisinger, Moss, & Clark, 2018).

In the literature on ways to improve health outcomes, there is a focus on maintenance visits for chronic illness because of the potential for such illnesses to quickly destabilize causing significant long-term health problems. A study of dialysis patients in the US found

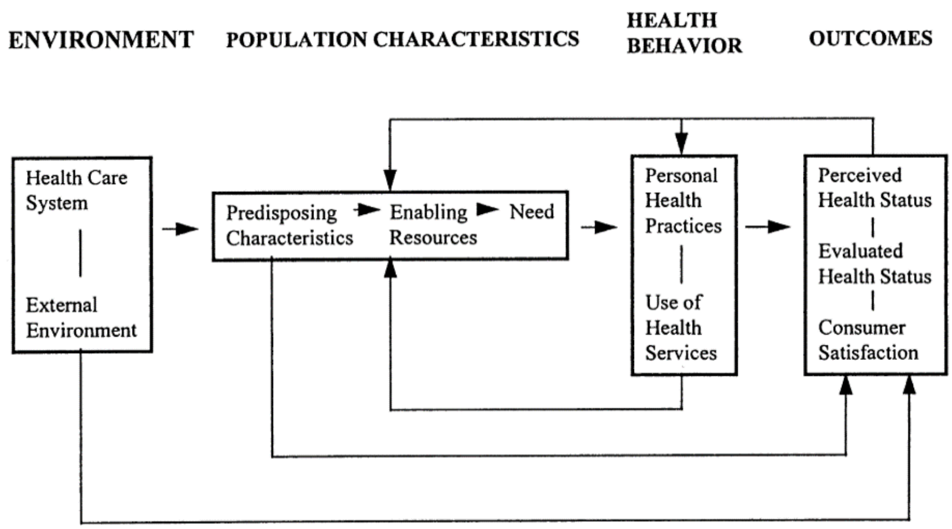
Table 6.1 Conditions most prevalent for those who miss care (R. Wallace, Hughes-Cromwick, Mull, & Khasnabis, 2005)

• Obstetrical care (including prenatal, delivery, and postnatal care),	• Depression and mental health,
• Cancer treatment and screening,	• Diabetes,
• Screening for high cholesterol levels,	• Renal disease,
• Screening for high blood pressure and hypertension treatment,	• Heart disease,
• Arthritis,	• Medical allergies,
• Asthma,	• Pain or aching joints,
• Chronic obstructive pulmonary disease (COPD),	• Poor circulation, and
• Dental problems,	• Vision problems.

that a missed treatment increased the risk of emergency room visit or hospitalization by a factor of two to four (Chan, Thadhani, & Maddux, 2014). In a study of a large ($n = 84,000$) sample of diabetic patients, frequently missed appointments correlated to poorer glycemic control and suboptimal diabetes self-management practice (Karter et al., 2004). Being poor also correlates to more emergency room visits, increased *no-shows* for medical appointments, and poorer glycemic and cholesterol control (Thomas-Henkel & Schulman, 2017). Missed methadone doses are particularly problematic because of the sensitivity of the dosing during treatment (Ball & Ross, 1991).

In trying to mitigate these effects, researchers and policy makers have been trying to better understand the underlying causes and barriers. The Andersen healthcare utilization model, developed in 1968 by Ronald M. Andersen, is a conceptual framework identifying factors that influence healthcare utilization and placing them into three categories: predisposing factors, enabling factors, and need. Predisposing factors include characteristics such as race, age, and trust in healthcare institutions. Enabling, or structural, factors include access to health insurance, transportation, time availability, and family support. Need includes both perceived and actual need for healthcare services (Andersen, 1995). His model (Figure 6-5) incorporates external factors, now commonly referred to as social determinants of health. Some factors directly influence health, such as air pollution, while others indirectly impact health through other mechanisms such as low quality public transit that impacts healthcare utilization. Anderson argues, "in revisiting the behavioral model, I am convinced that it does matter for sociologists to be involved...with studies of health services' use and access to care... to [examine it] from a comprehensive and systemic perspective." For this reason, I chose to provide data from the interviews in the form of case studies in order to provide a more contextualized understanding of various elements of the individuals' lived experiences.

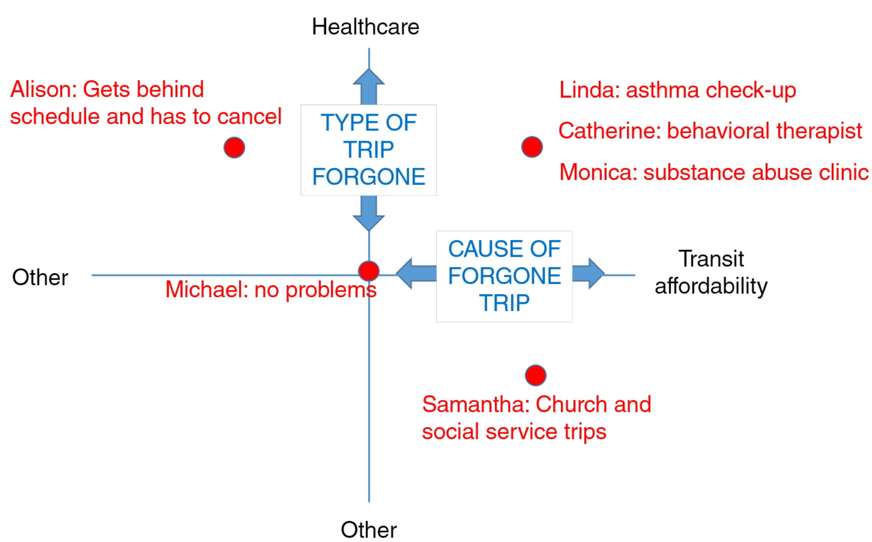
Figure 6-5 Anderson's *Emerging Model* of healthcare utilization (Andersen, 1995)



There is evidence from the interviews that routine visits are the types of healthcare appointments that are occasionally forgone, and that public transit cost is a factor. Chapter 7 presents the finding that once a transit pass product is purchased, individuals no longer consider the affordability of each trip. That finding applies here as well. From the interviews, I found evidence of skipping healthcare appointments only when paying for trips individually, not when using a pass, and individuals cited transit affordability as a cause for missing chronic healthcare appointments. These participants were being treated for different chronic conditions including: mental health (therapy), substance abuse rehabilitation, and asthma. Participants who discussed treatment for other issues, such as cancer treatment and a knee replacement, did not indicate that the cost of transit was an obstacle to access.

The following cases represent a selection of interviewed participants who indicated during the interview that they had recurring healthcare appointments. They were chosen for their representative breadth of different types of healthcare trips needed and how they reported transit affordability as a factor in missing trips. The cases can be considered along two dimensions. The first is whether they reported missing healthcare visits at all or reported forgoing other types of trips. The second dimension is whether affordability, or some other factor, was the primary contributor (Figure 6-6). Three of the cases describe missing healthcare visits because of affordability (Linda, Catherine, Monica). One misses healthcare visits because time management (Alison), and two do not report missing healthcare appointments at all (Michael, Samantha). These cases are not meant to be statistically representative but rather to illustrate variety. Some thematic observations are discussed following the cases.

Figure 6-6 Interview cases



6.3.1 Transit affordability impacting healthcare

Linda. *Linda has several chronic illnesses and sometimes skips her regularly scheduled appointments when she exhausts her transportation budget for the month and is afraid of not having enough money for food. She does not want to switch to a health-care provider in closer proximity to her home.*

An African American, Linda, 47, lives in Malden with her husband, but often overnights at her mother's house in Milton. She has been unemployed since she left her job as a nurse for the VA hospital working with cancer patients about 10 years ago when her younger brother was tragically killed at a construction site. Being quite close with her brother, she has not been able to recover from losing him. "I walked right out of my job, I didn't even think twice about it. I lost my mind for almost six months. That was my world. That was my baby boy. Because he was younger than me, I took him everywhere with me." When asked how easy it would be to get work as a nurse she said easy, "but I'm in too much pain lately with my legs and stuff. I'm trying to take care of me and my mother. She has rheumatoid arthritis, chronic allergies, and suffers from sleep apnea. I'm only 48 but my body feels like it's 88. I've done a lot of running in my days." She self-reported her health as *good* on the intake survey, which is incongruent with her verbal description.

Linda has healthcare appointments at Codman Square Health Clinic twice a month (though sometimes more frequently) and occasionally goes to referral appointments at Boston Medical Center. Both Codman Square and Boston Medical Center are transit accessible for her with a bus route very close to her house which takes her to the Malden center subway station, however, the journey takes about one hour. Though she moved to Malden many years ago, she continues to use Codman Health because she does not want to change healthcare providers. "Usually when I have an appointment at Codman Square I'll stay at my mother's the night before so it's easier." From there, she has two transit options, either trolley-to-bus or bus-to-bus.

At the beginning of the month, she sets aside $20 cash for bus fare for the month. She reported that she will skip an appointment occasionally because she has used up her monthly allotment for transportation, and then just go the next appointment two weeks later. I probed to understand whether funds were ever taken from other budget items. She said sometimes she is afraid of not having enough money for food so opts not to spend more on transportation. This usually happens toward the end of the month. There was an additional dilemma she described. Because the small grocery store walking distance from her house is significantly more expensive, she prefers shopping at Market Basket in Revere but that requires a bus fare in each direction so often overspends on food when she goes the local market. Linda did indicate that sometimes a bus driver will let her on without paying, especially for the local route by her house, but that is not possible at the subway station, so does not help with the journey to her healthcare appointment or to her mother's house. When asked about whether anything changed during the study when she was using the discount smart card, she said she visited her mother more often because she didn't feel it was costing much for each trip, and she did not recall missing any healthcare visits during that time.

* * *

Catherine. *Catherine's financial situation keeps her thinking in the very short term which sometimes leads to skipping healthcare appointments as well as other activities.*

Catherine is a 26 year old African American currently in school at community college. She has been diagnosed with chronic fatigue syndrome. Her medical appointments at are at different locations. Her primary doctor is at a family clinic walking distance from her home in Mattapan. She recently changed locations from the clinic that she used since infancy, which was a difficult decision, but allowed her to go to all her appointments without having to worry about paying for the bus. “What constitutes an okay or not okay appointment to skip? Let’s say I had to go to [my therapist] which requires taking the T to get there, it’s like, I might need to go to therapy for my mental health to be solid, because if I don’t catch this two week appointment, I’m not going to see her for another month, but if I can’t make it there financially, if I don’t have the weekly pass at the time, I’m likely to just skip it. Another thing is I don’t really want to go to therapy. I mean, who really, really wants to go to therapy. Just having one more thing to think about, whether I can get there, to reduce motivation.” For specialist appointments at Boston Medical Center, she also reports sometimes canceling appointments. “Sometimes I’ll have to just not go. I call them and reschedule for another time and then I’ll just pray that I have the money by the time that happens.”

Financial uncertainty seems to play a role in dictating trips. “Usually people in my circumstance, if someone gives me $20, okay, I can eat and I can take the bus a few times on that.” She generally does not get the weekly pass and makes travel decisions based on funds available at the moment. “Once, one of my friends gave me a gift of $100 and when I’m thinking about that hundred dollars, there’s no way that the first thing that’s going to come to my mind is going to buy an $85 [monthly] T Pass.” She acknowledged that her decisions are not always seemingly rational when looking at them in hindsight, such as choosing to take the bus to sing in the choir rather than use the fare to go to a medical appointment, but at the time she went with what she thought would make her happy in the short term. During the study she bought the $30 monthly pass using her discount smart card. Reflecting back on that time, she reported feeling more free to do the things she needed and wanted to in life without having the extra thought process. In an example of her planning longer term, she signed up for a support group because she knew she would be able to get there for each meeting. "I guess I could plan ahead more freely. Because I wasn't planning in a cost way." When the study ended, she reflected on how it felt. "It definitely made me more aware how much public transportation affected my life and how much the mental energy regarding budgeting for transportation affected my life."

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Monica. *Monica sometimes doesn't have cash in hand to get to her substance abuse clinic appointments. The uncertainty as to whether the shelter she is in will have MBTA fares to hand out adds to the instability of her situation.*

Originally from the South Shore, Monica has been living in Boston since high school. She lives in a women's shelter in Roxbury with her infant son and currently has methadone clinic appointments several times a week. She spoke of how she often runs out of money before the end of the month. Though she sets aside transportation money each month, it often does not last. In addition, there are times when she is hoping to get a few free single-ride CharlieCards from the shelter or other social service center but they are out. Under these conditions, she said she sometimes skips her clinic appointments because she does not have the cash to ride the bus.

From her descriptions, I identified a dynamic that was occurring such that the uncertain availability of the free CharlieTickets led to her take a *hope for the best* approach to decision making, spending money in the present hopeful that it would work out. Many times it did, but not always. She describes her experience accessing free single-ride CharlieTickets. "They'll get like a bunch of [single ride CharlieTickets] in the beginning of the month and you can ask for them if you need them and they'll give you a couple. You can ask them like once a week, and sometimes they'll give you a couple more, depending on who it is.

Sometimes they'll just give you one but sometimes two. But sometimes they would be gone, you know, before the end of the month...Yeah, so you can't be like that last minute type of person if you really need one of the bus tickets now in case they don't have any. Lots of times they do, but many times they don't, you never know."

She also indicated that she sometimes would spend money on taxis which would quickly deplete her transportation budget. She describes paying for taxis when returning home from a meeting at night when it is dark out because she does not feel safe taking the bus back at that hour. "I mean I could take the bus, but I just would rather not. So if I have the money in my pocket, I'll spend it to get home in a taxi. I know I probably should save it, but I just hope they will have some CharlieTickets for me in the morning. And maybe I shouldn't have gone out in the first place, but I can't just sit around all the time and do nothing." Returning to the pass versus pay per ride issue discussed in Chapter 7, the possibility of free CharlieTickets leads her to avoid purchasing weekly passes which could serve as a stabilizing force in her life.

6.3.2 Healthcare appointments missed for other reasons than inability to pay for transit fares

Alison. *Alison occasionally misses regularly scheduled healthcare appointments because the is often running late. She does not report the cost of public transit as an issue.*

Alison is a 39 year African American single parent with two young children ages three and seven living in Lower Roxbury. She is currently unemployed but attends a training program three days a week and is looking for work. Her housing, provided by the Boston Housing Authority, is about a 15 minute walk to a nearby subway station or a major bus hub, and a 5 minute walk from the Silver Line bus on Washington Street. She has healthcare appointments twice a week at different locations. One appointment is for opiate addiction recovery and the other at a therapist. It takes about 45 minutes to reach either location by transit from her home. As a side note, she takes advantage of being at these locations to go to the fish market or grocery shopping at Market Basket to save on food costs. Occasionally if she is running late for a healthcare appointment, she takes an on-demand ride from either Uber or Lyft (no more than once a month) at a cost of about $15 one way. This, she expressed, creates anxiety because she always feels it is at the expense of being able to take her sons out to places like the Museum of Science (where admission for SNAP recipients is only $1) or to birthday parties that sometimes require taking an on-demand ride service home after dark. My continuous, but gentle, probing into whether she ever misses appointments finally yielded that it does occur occasionally, her body language exhibiting embarrassment as she discussed reasons for missed appointments. Most of the time a missed appointment occurs when she gets behind schedule dropping off her younger child at daycare, but can also occur when the bus or train is late or slow en route because of traffic and thus arrives late at her destination. Toward the end of our discussion in missed appointments, she revealed in a lowered voice, that sometimes it had occurred in the past when she was at a low point and had no money at all. She did indicate that, "there was one time that I was able to reach out to my therapist and she was able to send a ride out to me. But that was only once." My impression is that in the case of Alison, most of the missed healthcare appointments are caused by factors other than the cost of transit, though that has occurred in the past. She often copes by asking for money from other family members.

6.3.3 Transit affordability an issue but not for healthcare trips

Samantha. *Samantha is experiencing a significant, but hopefully short-term, financial crisis. She was diagnosed with cancer while at the same time was in need of a second knee replacement. Because of very limited available funds, she reported regularly forgoing trips to* *church and a community resource center. She sometimes cancels healthcare appointments because of the cost of the co-pay not specifically because of transportation costs.*

Samantha, born in Jamaica, is a 59 year old single woman currently residing in Dorchester. She has carpal tunnel syndrome and also has problems with her knee for which she wears a brace and uses a cane, but said, "I'm trying to do without the cane." The orthopedist knee appointments were challenging to get, sometimes requiring a 3-month wait, so she avoids missing those. In discussing her budgeting priorities, she indicated, "after rent, I think about transportation even more than the phone, you know because if you don't have a car, to get around, I always want to make sure I have transportation." For a brief period, she reported canceling appointments primarily because of an inability to afford the $25 co-pay. These financial problems began about a year ago when Samantha was diagnosed with cancer and had to take a leave of absence from her job working with troubled young men in classroom and group-home settings. This was the point at which things fell apart for her. She quickly depleted her savings while waiting to be approved for disability. At the time, all she received was $306 per month food subsidy from SNAP. "When you're working and things are going good and your check is going into direct deposit every week, that is so much money. But wait till you're not working. In three months in six months, you're down to $1000, $2000. And after another month you have no money. Oh my I never believe $10,000, $12,000, could go so quick. And I didn't buy anything, no shirt or shoes, nothing. It went just like this. A couple of times, for a couple of bills I had to go into my retirement plan. They charge you so much tax like if you want $1000 or $1500 and the government is taking like $500 each time and I wanted to cry. I thought what I could do with $500 because I was destitute, I was broke."

Even now that she receives the disability check, she struggles to make ends meet. In reflecting on paying for transit, she says, "it all adds up quickly, you know, those $3.40.

After my appointment with you today I'm going to go help this young lady for the polling station tomorrow, that's $3.40 and then I'm going to the Boston Medical food pantry and then home, another $3.40." She described two types of trips that she regularly skips because of not having enough money to pay for transit. One is going to evening meetings at her church on Wednesdays and the other is going to Rosie's Place where she can use the computer to compose poetry. She expressed significant disappointment when recalling times when she missed these activities. When using the discount smart card during the study, she reflected on the joy she experienced not having to consider limiting her travel to save money. She is almost finished with her chemotherapy treatments and hopes to get back to work soon.

6.3.4 No issues with affordability

Michael. *Michael has regular standing medical appointments but does not indicate that transit affordability is a barrier to getting to these appointments. He reports having significant anxiety and, as such, does not miss appointments and is always on time.*

Michael is a 31 year old male who identifies as African American and lives in Mattapan. He has two children from a previous marriage and visits them once a week in Brockton where they live with their mother. Those trips require taking the *BAT* bus operated by the Brockton Area Transit which is a separate authority such that the discount study card did not provide a discount for that service. He is unemployed and has been since early 2019. He had previously been working at a restaurant in Cambridge and, though he is looking for work, it is unclear how much effort he is currently expending on the search.

He has two separate standing monthly healthcare appointments both at Boston Medical Center and has had these two appointments for about 5 years. One is with his therapist and the other with his primary care physician, although he did not indicate why he needed to visit his primary care physician monthly. It is unclear what circumstance led to establishing these appointments initially. When asked whether he tries to schedule them on the same day for convenience, he replied that coordinating would be a challenge because of the providers' limited availability. Even if scheduled the same day, the appointments would likely be hours apart, and Michael is not interested in spending extra hours at the medical center. He did not seem bothered by traveling to the two appointments on different days.

Getting to Boston Medical Center from Michael's house by public transit takes about an hour. He has several different transit options involving combinations of trolley, subway, and bus. Some of the options require more than one transfer such that two fares are required for travel in only one direction. One of the options does not require a second fare but involves additional walking. For the first month of the study period Michael purchased a monthly pass and for the second he used his smart card to pay for each trip individually. Looking at Michael's smart card data, comparing similar trips made when he had a monthly pass and when he paid for individual trips, it appears likely that he did not pay for all the legs of each journey. Hence, his cost was one single fare for the journey (utilizing one free transfer), suggesting that cost is a factor, but that he gets around the double fare problem.

He rated his health *excellent* but indicated the highest level of stress for both of the self-reported stress questions. When asked what happens if he is running late for one of these appointments, he indicated that he takes a Lyft as a last resort. "So I almost never want to be running late. But if in doubt, I'll click it and hate myself later." He says he never misses appointments: "I like try to keep my itinerary going. I get mad at myself if I don't. It will send me into, like, a downward spiral if I'm late." At other points during the interview, he mentioned friends that refer to him as "a little control freak." It is, then, unsurprising that he is diligent about going to his appointments in order to avoid exacerbating his already high stress levels. Interestingly, he did not mention the unreliability of the MBTA as a cause of stress, it seems might have been expected. It appears that for the most part, Michael is able to keep his stress under control through time management.

6.4 Conclusion

Using a combination of quantitative and qualitative methods, this chapter investigates in more detail the challenges low-income individuals face in accessing healthcare. Results from the randomized controlled evaluation indicate that providing a transit discount leads to more healthcare trips. A regression model investigates this finding in more depth by including demographic and self-reported health scores at baseline. Because the number of healthcare trips taken is a count variable with a high percentage of zeros, a zero-inflated negative binomial regression model is used.

I found that there was not a correlation with the rates of healthcare related trip taking, but that individuals rating themselves in *fair* or *poor* health correlated with reporting one or more healthcare trips over the course of the study. This highlights the usefulness of a mixture model to analyze data sets with a high proportion of zeros. The findings align with the hypothesis that those in poorer health are more likely to be seeking medical attention than those in better health. This might be attributed to the small study time period of two months, where a longer study, such as one year, might detect regular appointments for those in good health that are more likely to have been missed in my study.

Semi-structured interviews with study participants bolstered the quantitative finding that transit affordability is a factor in healthcare access. Interview results also indicate that chronic healthcare visits are affected and contextualize this finding within the lived experiences of study participants. With chronic conditions more prevalent in low-income populations, this is a particularly important finding. The types of chronic illnesses varied but included asthma, substance abuse, and therapy. Fare affordability as a cause of missed trips, though, was not universal. Some respondents did not indicate missing healthcare appointments at all, and others attributed the cause to factors such as time management. There was no evidence that acute visits were impacted. Not surprisingly, affordability presents itself within the context of differing individuals' personalities and the particularities of their lives. Though measuring access to healthcare is one step closer to measuring impact on health or quality of life outcomes, an assumption that more trips to healthcare correlates to improves outcomes is still needed. The health literature bridges this gap by indicating that missed healthcare visits for individuals with chronic conditions is a particular concern and leads to poorer health outcomes.

7

Paying the fare

This chapter explores the behavior and decision making that impacts how low-income riders pay for their transit trips. Behavioral science theories are applied to the findings to better understand how individuals make decisions in the context of transit affordability. The first section introduces the behavioral science concept of the *scarcity mindset*, the core premise being that poverty causes reduced cognitive function and subsequent poor decision making. The second section presents findings on observed behavior, from smart card usage data, regarding how individuals pay for transit focusing on three areas: (1) using unlimited passes versus paying for trips individually, (2) patterns for reloading smart cards with additional cash value, and (3) fare evasion or underpaying when using cash on the bus (i.e., *short* fares.) The third section proposes a two-tiered decision making model to explain how pass products impact transit utilization rates of low-income riders. I then provide results from an analysis that integrates participant smart card data with data from interviews to suggest that individuals' behavior appears to fall into two categories: *attentive* and *inattentive* planning. The chapter concludes with policy implications of the findings.

7.1 Scarcity mindset

Behavioral economists have recently been studying how and why the behavior of those with limited means differs from that of others. Their core thesis is that poverty causes diminished executive function, short-term thinking, and difficulty coping with shocks, and it is this *scarcity mindset* that leads to suboptimal outcomes.

The field of behavioral science calls attention to the flawed assumption that humans always act rationally. It focuses on understanding the effects of psychological, cognitive, emotional, cultural and social factors on people's decision making. In particular, choices made under conditions of uncertainty are poorly modeled by conventional utility theory (Kahneman & Tversky, 1979). The insights generated are not necessarily surprising; indeed they can often be found in existing social psychology literature. But the importance of this work entering the mainstream of transportation economics has been to counter traditional rational models of human behavior that have previously dominated policy making. Social scientists have discovered in the last half century that context has an enormous impact on behavior.

Broadly, researchers (and people in general) regularly proffer examples demonstrating that low-income individuals make "bad" decisions that are not aligned with either externally- or internally-defined self interest. Low-income individuals do not access preventive health care, keep up with medical treatments, or attend to appointments at the same rates as others. They are accused of not eating well, poorly managing their finances poorly, and a variety of other behaviors. It is no surprise, then, that many believe those in poverty and on welfare are responsible for their situation because they are flawed in that they lack effort, thrift, morality, and ability (Ganz, 2011; Kluegel & Smith, 1986). Behavior is viewed as being derived from a "culture of poverty" rife with deviant values, or from ignorance caused by less formal education (Katz, 1990). It would logically follow that remedies should take the form of paternalistic guidance and support. An alternate explanation suggests that poverty is the result of structural flaws in society combined with luck and circumstance. In this view, poor individuals are neither inherently defective nor completely responsible for their condition, and their behavior is as rational and informed as anyone's, driven by calculated adaptations to their present circumstances (Bertrand, Mullainathan, & Shafir, 2006).

Behavioral economists have recently entered the fray by providing alternate theories that in a sense form a bridge between the aforementioned dichotomy. They suggest that although those with limited means do not appear to make decisions as rationally as those more well off, this is not the result of inherent character flaws. Some behavioral economists suggest that poverty itself shapes this behavior described as the *scarcity mindset*. Low-income individuals are less successful in various aspects of life because living in poverty impedes cognitive capacity, not because those living in poverty are inherently less capable. We fail to recognize that we are far more limited in terms of our cognitive capacity or bandwidth than we believe:

> "So, you do studies that some of them are quite comical, there's a whole battery of studies where basically [they] have half of you retain a 2 digit number in your short term memory, so please remember 'one-seven,' and the other half has to retain an 8 digit number, please remember 'one-seven-two-four-two-six-five-two.' And when we do that, after a few minutes we observe all sorts of behaviors. Those who are retaining the 8 digit number eats less healthy, are less likely to notice somebody dressed as a clown on a unicycle, any way you look at it, it's stunning how much less you are able to do just being busy keeping those 8 digit number in your head."[23]

In the book *Scarcity*, authors Mullainathan and Shafir posit that scarcity is a more fundamental explanation of human behavior than competing theories which focus on culture,

[23] Eldar Shafir, excerpted from the Dec. 2, 2016, congressional briefing hosted by the American Planning Association in conjunction with U.S. Rep. Barbara Lee, D-Calif., titled "The psychology of poverty: How scarce resources affect our behaviors and decisions, and what we can do about it."

personality, preferences, and institutions. The positive side of scarcity is that it forces focus (Mullainathan & Shafir, 2014). For example, when deadlines loom, people are forced to make difficult choices that otherwise would be left lingering. Creative bursts and significant innovations often occur under duress (what they term a *focus dividend*). The negative side is more concerning: scarcity reduces bandwidth leading to both an inattentiveness to important things outside of the short-term and immediate focus and a reduction in executive function. Excluding things outside of the present crisis leads to behaviors that end up reinforcing scarcity. Preoccupations with the constant juggling of competing budgetary conflicts leave fewer cognitive resources available to guide choice and action. Focusing on too many things leaves one less able to consider other goals.

> "The poor must manage sporadic income, juggle expenses, and make difficult tradeoffs. Even when not actually making a financial decision, these preoccupations can be present and distracting. The human cognitive system has limited capacity. Preoccupation with pressing budgetary concerns leaves fewer cognitive resources available to guide choice and action. Just as an air traffic controller focusing on a potential collision course is prone to neglect other planes in the air, the poor, when attending to monetary concerns, lose their capacity to give other problems their full consideration." (Mani, Mullainathan, Shafir, & Zhao, 2013)

Much attention has been given to the hypothesis that poverty negatively impedes cognitive, or *executive function* (Mani et al., 2013; Shah, Mullainathan, & Shafir, 2012). Executive function skills play a critical role in helping people focus on multiple streams of information simultaneously and revise plans as needed. Those experiencing cognitive overload exhibit difficulties meeting deadlines, prioritizing and following through on tasks, arriving on time, organizing their work, and have difficulty seeing new ways of doing things. Procrastination, planning, and self-control are related to the tendency to focus on local decision contexts. Table 7.1 summarizes these skills into cognition and behavior categories. Several of these elements are the focus of the analysis presented in the next section regarding how decisions are made regarding spending on public transit— in particular, planning, prioritization, organization, meta-cognition, and task initiation. Although poverty impacts cognitive capacity, it does not mean that those experiencing poverty are inherently different from anyone else. Indeed, many of the decision-making weaknesses described above apply to people from all income categories (Bertrand et al., 2006).

Table 7.1 Executive function skills

Skills Involving Thinking (Cognition)

- **Working memory:** Ability to hold information in memory while performing complex tasks; incorporates ability to draw on past learning or experience to apply to current situations
- **Planning/prioritization:** The ability to create a roadmap to reach a goal or to complete a task; making decisions about what's important to focus on
- **Organization:** The ability to create/maintain systems to keep track of information or materials
- **Time management:** The capacity to estimate how much time one has, how to allocate it, and how to stay within time limits and deadlines
- **Metacognition:** The ability to monitor oneself; ability to ask oneself: how am I doing/did I do?

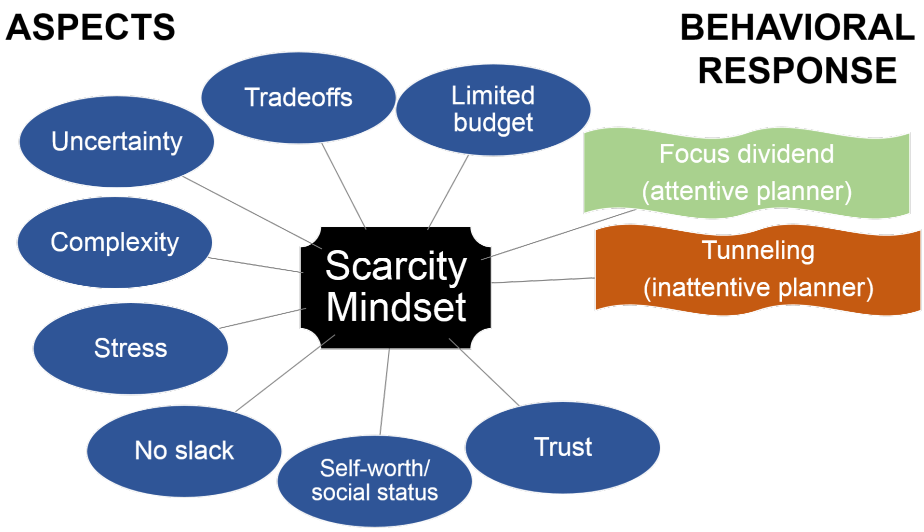
Skills Involving Doing (Behavior)

- **Response Inhibition:** Capacity to think before you act
- **Emotional control:** The ability to manage emotions to achieve goals, complete tasks, or control and direct behavior
- **Sustained attention:** The capacity to keep paying attention to a situation or task in spite of distractibility, fatigue or boredom
- **Task initiation:** The ability to begin a task or activity without undue procrastination and to independently generate ideas, responses, or problem-solving strategies.
- **Goal-directed persistence:** The capacity to have a goal, follow through to the completion of the goal, and not be distracted by competing interests
- **Cognitive flexibility:** The ability to revise plans in the face of obstacles, setbacks, new information, or mistakes

Source: (Dawson & Guare, 2009)

The scarcity mindset model is summarized in Figure 7-1. Mullainathan and Shafir describe the following core aspects: having limited financial resources, constantly juggling tradeoffs, living with uncertainty, increased levels of life stress, and not having the slack to manage the unexpected. The behavioral responses come in two forms: the *focus dividend* which brings heightened attentiveness to the decision making process, and *tunneling* which creates inattentiveness and less thoughtful decisions.

Figure 7-1 The scarcity mindset model



Limited budget. At the core of the problem is the scarcity of money. At a certain point, no amount of frugality will solve the problems associated with not having enough to go around. For this very reason, there is a growing movement to consider a universal basic income, which could comprise supplements based on a work requirement (a more American approach), or a traditional social assistance model used in many European countries. In urban areas such as Boston, the cost of living is skyrocketing, and since the Federal Poverty Standard has not kept pace with Boston's cost of living, the *officially poor* are poorer today than they were 20 years ago.

Scarcity refers not only to lack of money, but also to lack of time. Time is a commodity often used by those with limited incomes as compensation for lack of money. For example, a low-income individual may choose a longer transit routing option involving only buses to avoid the higher cost of a route that includes a subway leg. Victoria, a participant in the study, described this behavior to save what others might consider small amounts of money.

"I go to church early in the morning. Usually I take the 15 or the 45 [bus] to Ruggles, then catch the Orange Line [subway] to Forest Hills, then catch the 32 to Hyde Park to my church. But the past month, I found another way, I've been walking from my house a ways and then take the 16 [bus] to Forest Hills and then take the 32 bus to Hyde Park. So that way, I save about 75 cents. It takes longer but I just have to accept that."

Tradeoffs. Low-income individuals trade time and convenience for cost. But constantly having to think through tradeoffs of how to spend money and knowing the potential risks involved can be exhausting. Consideration of tradeoffs is not unique to any single economic demographic. Middle-class people make spending decisions such as whether to eat at home or spend money going out to dinner, whether to take a taxi or wait for the bus, or whether to buy something at the store or order it online. However, low-income individuals make these tradeoffs far more frequently between core living expenses, not luxuries. The scarcity mindset theory suggests that for many, this constant decision making becomes debilitating.

Uncertainty. Income fluctuation is a common form of uncertainty for low-income individuals. Juggling multiple part-time jobs with uncertain hours is one example. Thus, there is a concern about investing in something now, such as a transit pass, which ties up funds that may be needed later. As a result, a conservative shot-term decision might be safer but more costly in the long run (Tversky & Kahneman, 1992). Low-income individuals often overestimate the probability of future gains, such as hoping for rides or free transit from social service providers. Such exaggerated expectation, also called *optimism bias* might lead to a decision not to purchase a pass product and spend the money on other more pressing needs.

When asked about using a debit card, a participant named Jasmine replied, "Oh, I get a prepaid [debit card]. And that's what I do with my money, I don't put my money in a bank I put it on a card. That way it's handy and I always have it. And in case of emergency, I don't have to worry about the bank or ATM, but my mother keeps the cash safe, it's safe over there." Those who have not personally experienced poverty have difficulty relating to this behavior. One might ask, "how hard could it possibly be to get to an ATM in an emergency, they are everywhere." This questioning, though, misses the point: the feeling of comfort and control Jasmine exhibited through her rationale is influenced by perceptions of the reality of one's own lived experience. Something irrational to an outsider might be perfectly rational to the individual making those choices.

Interviews revealed that many individuals have the potential for others to provide a ride for a future activity but with unknown certainty. As a result, people choose not to purchase a weekly pass in the hopes that those rides will materialize. Sometimes when visiting his son, Irving's ex-wife will drive him home, meaning he doesn't need to pay for transit for that trip. "Sometimes it'll get late, and I'll get dropped off. So I could take a trip out. But I don't know ahead of time, so it's hard to know whether to get that weekly pass or not." In economic terms, low-income individuals exhibit a higher discount rate than others because money being used to take care of a current need or crisis is more valuable than the projected future use of those funds (Carvalho, Meier, & Wang, 2016).

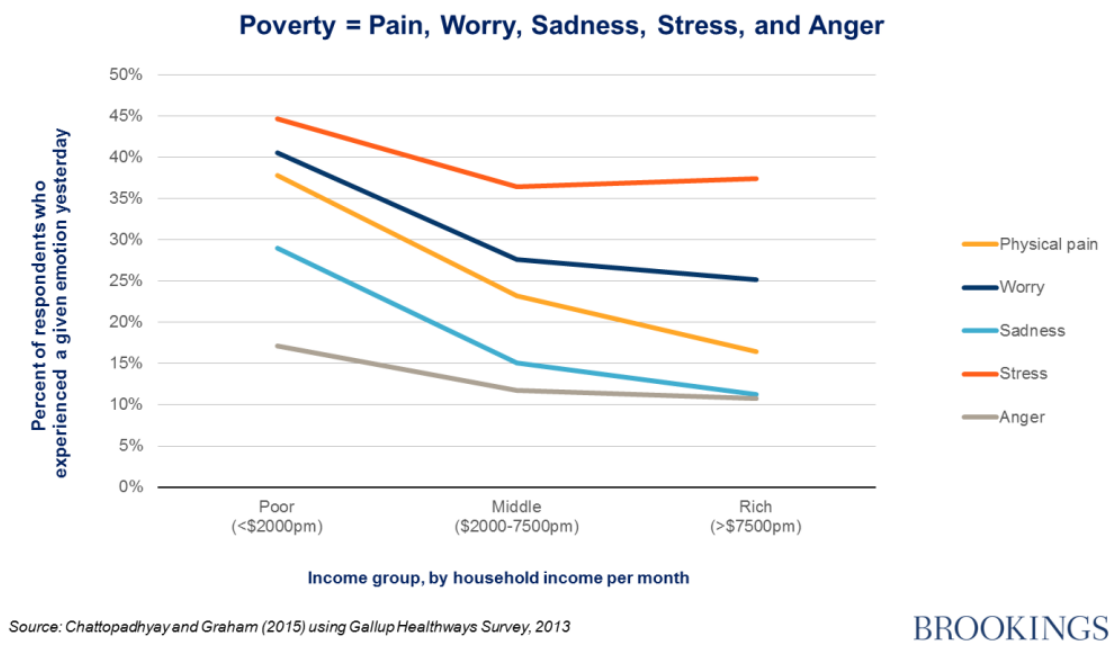
Another source of uncertainty is the inconsistent availability of single-use transit tickets which are sometimes available at shelters and social service agencies. Consistency is critical for effective planning.

Complexity. Navigating the world when poor is far more complex than generally acknowledged. To receive government benefits, for example, many requirements must be met involving a great deal of paperwork and bureaucracy. The many complex government systems can quickly become overwhelming. One of the differences between the private and public sectors is the institutional tolerance for complexity. Companies want simple, easy to explain options that results in more customers and better overall profits. They invest heavily in customer facing components such as user interface design and customer service workflows. Government, on the other hand, is hampered constrained resources, structures that do not align incentives for improvement, and politics that respond to public critiques on how tax-payer dollars are being spent.

For public transit, fare policies exemplify how complexity impacts low-income transit riders. It is well known that low-income riders attempt to take advantage of transfers to reduce costs (Perrotta, 2015). For example, the rules allow a bus to bus transfer as long as the second bus is on a different route. A bus – subway – bus transfer pattern is permitted. All transfers must occur within a two hour window. One participant describes how they navigate this process saying, "I have to know where all the different buses go and how often they come. Then I get myself to the first place I need to go, maybe that takes a half hour. So I got an hour and half left and hope I can get finished within that time and that the next but I need comes in time. It can be stressful trying to get it all to work, but I save $1.70 doing that so I gotta do it." I asked what happens if he is just past the 2-hour window when he gets on the bus and he replied, "that's tough, because the driver can't look at my [CharlieCard] and see that I'm just like 5 minutes over, and if I tap the card it just takes another $1.70 and there's nothing I can do about it, so it all comes down to trying to convince the driver of my situation but they just give you that look like 'sure, right,' so I have to pay and just feel really irritated I went to all the trouble and had to pay twice anyways." Another participant, Shawn, expressed that a change in transfer policy would be beneficial, "I personally believe the transfer time limit should be longer to help lower income riders take care of errands without rushing to receive the bus transfer."

Stress. Stress is another element to consider. Pain, worry, sadness, and anger are all significantly higher among low income groups than more wealthy ones (Figure 7-2). Research has shown the causal effects of stress on overall health (Selye, 2013). Additionally, research has shown that poverty and stress cause long-term biological harm to children in the form of neuroendocrine function, early brain development, and cognitive ability (Blair & Raver, 2016). This has altered the approach to early childhood development to include a more scientific understanding of brain development.

Figure 7-2 Negative life experience by income group



Source: https://www.brookings.edu/blog/social-mobility-memos/2015/02/19/the-high-costs-of-being-poor-in-america-stress-pain-and-worry/

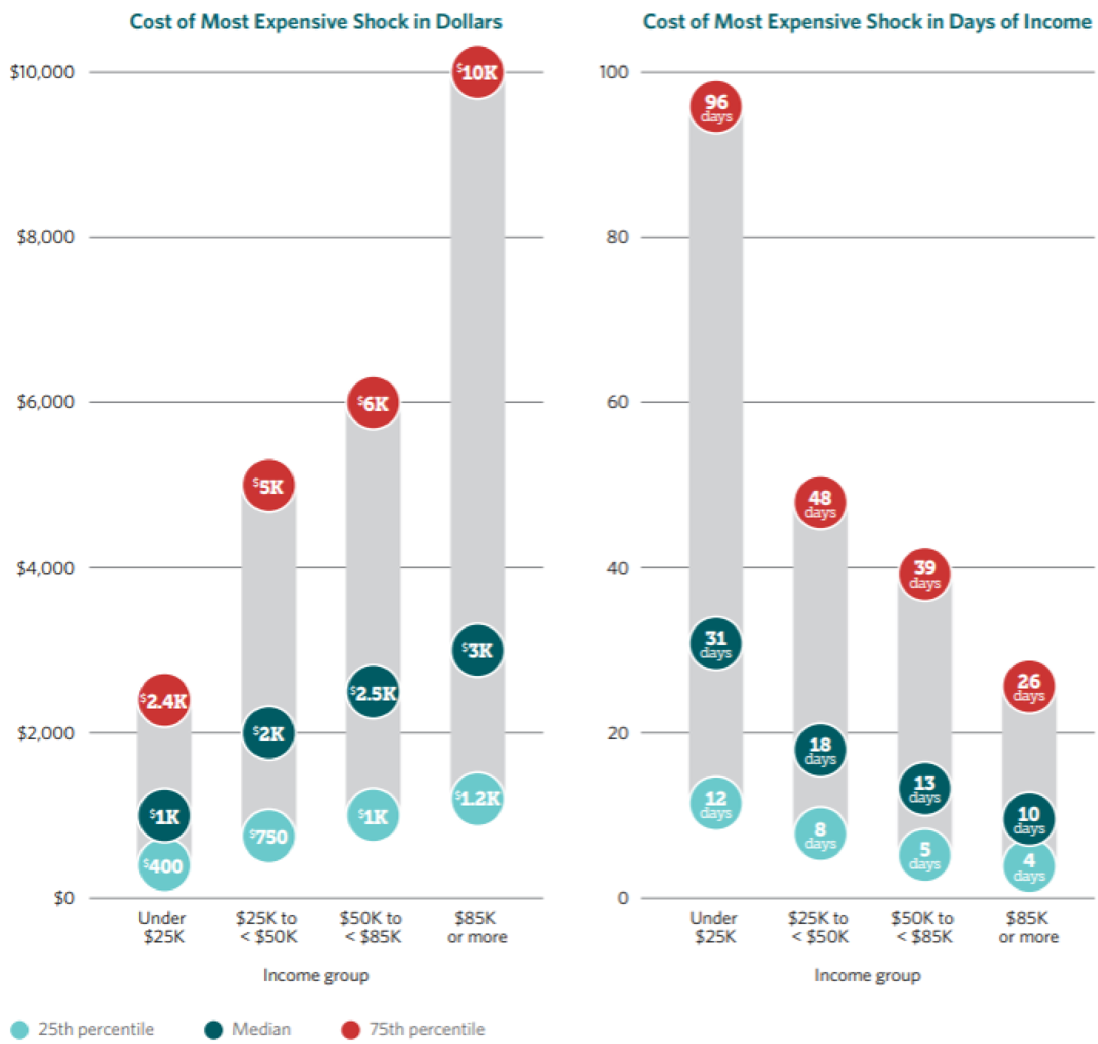
Having to think about the affordability of transit every single time a transit trip is taken creates stress for many participants. One participant, Alanna, described her thought process regarding getting a weekly pass. "I literally walk myself through the process: if you just get it, it'll enable you to feel freer, and you can go more places, and you'll be happy that you spent it, and not have to stress out every time you tap your [CharlieCard] and have money taken off. But in reality, my mind says: you need to go pick up your prescription from CVS, you need to be able to pay that copay. You just can't afford it."

No slack. The issue of cognitive ability is compounded by another aspect of poverty, namely that low-income individuals lack a financial cushion (or *slack*) during bad times. Even small income or expense fluctuations can lead to immediate hardships that can spiral out of control. Some researchers point to the lack of access or use of mainstream financial services (Barr, 2012). With limited access to savings, credit, or insurance, many resort to high-cost borrowing, which solves the crisis in the short-term, but further exacerbates the problem in the long term. Borrowing from friends and family is another common coping mechanism but this shifts the burden to others who are often low-income themselves. A behavioral science perspective emphasizes the psychological costs resulting from low and unstable incomes, and how small and momentary financial hurdles can cascade into long-lasting financial insecurity.

Pew Charitable Trust (PEW Charitable Trust, 2015) reported that 60 percent of US households experienced a financial shock in the past 12 months and that one in three have no savings at all. As shown in Figure 7-3, higher income households had more expensive shocks but shocks as a fraction of household income were a greater burden on lower-income households. About 75% of families with an income under $25,000 indicated struggling afterwards as a result of a shock compared with 35% of those earning $85,000 or more.

The following example comes from a study participant impacted by an unforeseen expense. "I don't go out as much now because money is limited. Last month, I had an issue with Mass Department of Taxation where they said I owed some money, it just came out of the blue, they didn't notify me, they just went into my [disability] check and took $380 from the $1500 [monthly disability check]. Oh my goodness, it was so traumatic because rent was due. I had to borrow but it still wasn't enough. I spoke to the landlady today and said I'm going to pay next month, I hope." It is unknown how this financial setback might play out in the long term. It did curtail her spending on transit which impacted her ability to get to the food pantry. The result was that she ended up spending additional money at

Figure 7-3 The burden of financial shocks (PEW Charitable Trust, 2015)



the convenience store nearby.

Finally it is worth acknowledging that low-income individuals have a harder time recovering from mistakes. Though we all make mistakes, poverty strips away the margin for error, so the results manifest themselves in more pronounced ways.

Self-worth/ status. Finally, there is the notion that low-income individuals spend a higher percentage of income on products and services perceived to have high status in order to restore feelings of self-worth. To an outsider, this can be seen as a surprising example of irresponsible spending in the face of scarcity. Some researchers found that low-income gregarious people spent more money on social status items than introverts (Landis & Gladstone, 2017). Decisions that support happiness in the near term, even if short lived, are made at the expense of financial freedom in the future. Scarcity often makes people feel powerless to do anything that will lead to long-term improvements.

This behavior also extends to the desire for car ownership, suggesting a negative association of public transit with self worth. Bratman et al. (2014) found that while wealthier people in the Washington DC area increasingly reduce their car dependency, poor people still aspire to car ownership. "This suggests that, for low-income people, cars may have merits beyond simple cost-benefit use calculations. Automobility remains a paradoxical cultural and status symbol, such that while wealthier people increasingly reduce their car dependency, poor people still aspire to car ownership." Their study found that African Americans were statistically more likely than other demographic groups to desire to own a car. Recent research suggests that many have implicit bias against buses, even those who don't explicitly claim such bias or even recognize it in themselves (Moody, Goulet-Langois, Alexander, & Campbell, 2016).

Most participants I interviewed indicated occasional use of on-demand taxi services such as Uber and Lyft.[24] Some said they had no choice because at times when they get out of work, there is not bus or train service. Others described Uber/Lyft rides as a luxury items. Selina talked about her occasional use of Lyft describing it as "treating myself when things are feeling really bad, rather than get on that bus and feel like a loser. I know I should just take the bus and use the money for food. But it just feels nice once in a while to just get into a Lyft like everyone else, there's nothing wrong with that."

Trust. Low-income individuals have a deep distrust for traditional banking. Research

[24] Lyft will accept prepaid debit cards while Uber requires only credit or bank-issued debit cards. Most participants mention Lyft, possibly for this reason.

suggests that they trust people more then they trust individual banks (Servon, 2013) which may explain a similar distrust of large government institutions like the MBTA. Despite their predatory image, payday loans, money-lenders, and check-cashers oddly enough offer low-income individuals a level of stability, trust, and personal customer service and flexibility that banks do not.

The academic Judith Levine (2013) notes: "distrust is really yet another form of inequality. Those who are better off have more reason to trust those around them. And that trust brings benefits ." Her interviewees described many welfare caseworkers as not taking the time to explain things clearly, not being respectful, and not following through on things they promised to do. She attributes this not to malintent, but because a caseworkers are under significant pressure with caseloads that are too large. Zacka (2017) concurs with this assessment, pointing out that, over time, this work environment "erodes and truncates the moral sensibilities" of bureaucrats. Levine emphasizes that this distrust is not an inherent or inherited "culture of poverty" characteristic but rather is developed through direct experience.

There is also evidence that the somewhat abstract nature of banking is a factor. A participant I interviewed, Rob, indicated that upon receiving his veteran benefits, provided on a debit card, he would immediately go to the ATM and withdraw the funds as cash. "I just like to be able to see it all to know that I have it and keep track of how much I have left." A combination of distrust for larger, impersonal institutions and fear of the potential for malfunctioning technology seems to influence the way low-income riders engage with the MBTA smart card-based fare collection system.

The following quote from Linda Tirado's Book *Hand to Mouth: Living in Bootstrap America* helps ground these somewhat analytical theories into the lived experience of someone who lived in poverty:

> "Why do poor people do things that seem so self-destructive? Poverty is bleak and cuts off your long-term brain. There's a certain pull to live what bits of life you can while there's money in your pocket, because no matter how responsible you are you will be broke in three days anyway. When you never have enough money it ceases to have meaning. I am not asking for sympathy. I am just trying to explain, on a human level, how it is that people make what look from the outside like awful decisions. This is what our lives are like, and here are our defense mechanisms, and here is why we think differently. It's certainly self-defeating, but it's safer." (Tirado, 2015)

Edin and Lein, in *Making Ends Meet* (1997), challenge our basic assumption about the manner in which welfare recipients make financial decisions by suggesting seeming irrational decisions are actually rational from a different vantage point. For example, many welfare recipients consider their child's present well being to be equally or more important than overall financial planning. This can result in decisions that seem to defy careful budgeting. Purchasing expensive name-brand sneakers may seem foolish, but single mothers explain that it deters their children from criminal activity that enable alternate ways to obtain the same sneakers. Going out to eat is explained by parents' recognition that their children need occasional treats despite the expenditure exceeding the monthly budget.

7.2 Observed behavior

7.2.1 Unlimited passes

There are two ways to pay for MBTA transit trips: purchase an unlimited pass, weekly or monthly, or pay for each trip individually. To begin, I examine how study participants paid for their fares. On average, they paid for 55% of trips by pass and 45% using cash balance (see Table 7.2). Control group participants who purchased a pass predominantly purchased the weekly pass (78%) over a monthly link or bus-only pass (21%). This is not surprising given that the weekly pass is one quarter the price of a monthly pass and that low-income individuals have reported preferring to spend smaller amounts at a time. Other researchers have similarly found weekly passes purchases at higher rates by low-income riders in Montreal, Canada (Verbich & El-Geneidy, 2017) and New York City (Hickey, Lu, & Reddy, 2010).

Table 7.2 Fare payment method

	STUDY PARTICIPANTS		ALL MBTA RIDERS	
	Control	**Treatment**	**Full Fare**	**Discount Fare**
Pre-paid cash balance	45%	46%	32%	29%
Pass	55%	54%	68%	71%
Weekly link pass	78%	*NA*	28%	*NA*
Monthly link pass	13%	100%	71%	100%
Monthly bus only	9%	*NA*	4%	*NA*
	100%	100%	100%	100%
Bus fare	$1.70	$0.85	`	$0.85
Subway fare	$2.25	$1.10	$2.25	$1.10
Weekly link pass	$21.25	*NA*	$21.25	*NA*
Monthly link pass	$84.50	$30.00	$84.50	$30.00
Monthly bus only	$55.00	*NA*	$55.00	*NA*
A "link pass" is valid for travel on bus and subway				

Pass purchase behavior of low-income riders in the study are compared all MBTA subway and bus riders, shown in Table 7.2. On average, 45% of trips by low-income riders were paid for individually compared with about 30% for the average MBTA rider. Control group participants paid for 55% of their trips using a pass product and used a weekly pass for 78% of those trips. Average MBTA riders paid for 70% of their trips using a pass product and used a weekly pass for only 20% of those trips.

Fewer than expected participants in the treatment group chose to purchase a monthly pass. This is surprising as the $30 cost was 60% less than a regularly priced monthly pass.

This supports the theory that low-income individuals are reticent to front funds to pre-pay for transit even if it saves them money in the long run.

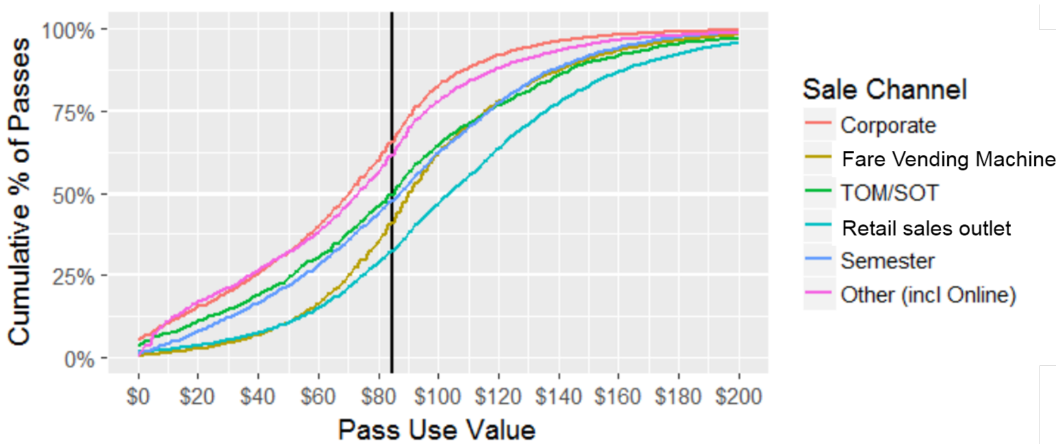
How many trips does one need to take in order to make purchasing a pass a more economical option? In the case of the MBTA, it turns out that it is a complicated calculation because of the complexity of the pass and differential modal pricing such that subway trips cost more bus trips. For individuals who take more bus trips than subway trips, the calculation is particularly challenging. This is summarized in Table 7.3. A participant in the control group paying full fare would need to take 13 bus trips or 10 subway trips per week on order to make the link-pass worthwhile, but only 9 bus-only trips per week for the monthly bus pass to be worthwhile. Someone in the treatment group paying discounted fares only needed 9 bus trips or 7 subways trips to make the discounted monthly linkpass economical. From a cognitive load perspective, there is a lot of calculation involved for an individual to assess the options.

Table 7.3 Minimum trips required to make a pass good value

	Min. bus trips /wk necessary		Min. subway (or combo with bus) trips /wk necessary	
	Control	Treatment	Control	Treatment
Weekly link pass	12.5	X	9.4	X
Monthly link pass	12.5	8.8	9.4	6.8
Monthly bus only	8.3	X	X	X

Between 30-60% of all MBTA riders who use monthly passes do not get the best value from them, meaning they would have been financially better off paying for trips individually. This range, shown in Figure 7-4, is based on how the passes were purchased. The upper bound of 60% (where the red curve intersects with the $84.50 pass cost) represents corporate pass sales. Because employers often subsidize employee passes, the best-value proposition is lower for these consumers. Unfortunately, there is no data connecting the amount of employer subsidy with the smart card pass identification to determine what percent of these riders are getting best-value out of their passes. On the lower end, 45% (brown line) represents subway station fare vending machine pass purchases and 30% (aqua line) represents convenience stores sales outlet purchases where individuals did not get the best value out of their passes. More low-income individuals purchase passes at retail outlets. 30% is still surprisingly high.

Figure 7-4 Percent of monthly passes that get "best value" across entire MBTA system organized by sales channel.



Sources: MBTA AFC, MBTA pass sale program administrative data
Notes: Includes passes that are sold but never used (use value = $0)

Data is for October 2016. Source: (Stuntz, 2018, p. 116)

One explanation for this behavior is the convenience of having a pass. After having obtained an unlimited use pass, one neither has to think about the cost for each subsequent trip nor ensure that enough balance is available on their smart card for each trip. This convenience might provide a psychological freedom that is more valuable to the consumer than the concern about getting the best value from the pass, and with pass programs automatically deducted from payroll, the payment is less noticeable and also requires effort to turn off and on.

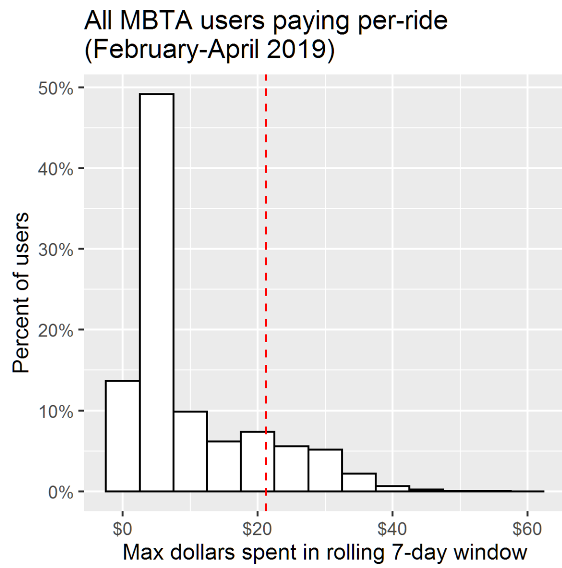
For low-income individuals, though, one might expect much closer attentiveness to the financial consequences of choosing whether to purchase a pass. But cash-flow issues might come into play. Riders who are extremely liquidity constrained, often referred to as *hand to mouth* consumers, may have difficulty fronting funds for a monthly pass and therefore pay more in the long term by paying for each trip individually. Advocates have long pushed for weekly passes to be one-fourth the cost of monthly passes to mitigate this problem.[25] Prepaying for a week of travel at $21.25 is far less of a burden than paying $84.50 at one time at the beginning of the month. A note regarding the different pass products: a weekly pass is valid for precisely 7 days from the moment of activation while the monthly pass is valid by the calendar month. The implication is that low-income individuals might leave gaps between the purchasing of weekly passes as a cost-saving mechanism. They could then focus on taking trips during periods when they were using a pass product.

To further an understanding of pass best value, I conducted the inverse of the above analysis, looking at all MBTA riders who were using their smart card on a pay per ride basis to see how many would have been better off purchasing a weekly pass product. I chose to analyze weekly instead of monthly passes because there is no penalty for purchasing a weekly pass instead of a monthly pass, and low-income individuals tend to choose weekly passes. I conducted the analysis by applying a rolling 7-day window across a two-month period (February and March, 2019). For each unique smart card used to pay for trips individually, I determined whether at any time over the period, an individual would have been better off purchasing a weekly pass. The results, shown in Figure 7-5, indicate about 15% of these users fall to the right of the $21.50 threshold represented by the red dashed line meaning they would have benefited from buying a weekly pass.

Conducting the same analysis for the participants in the study, I find that 30% of individuals in the study who choose to use their smart card to pay for trips individually,

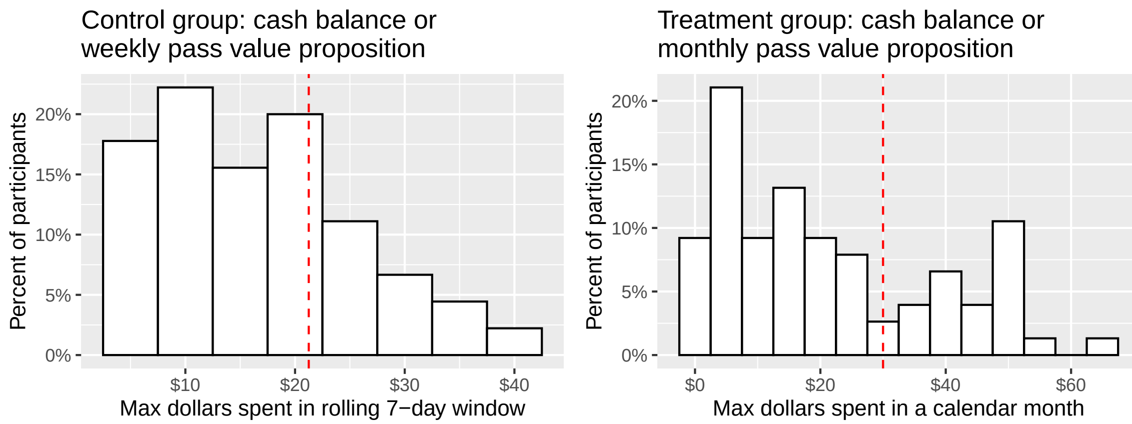
[25] During an MBTA fare increase in 2007, the cost of a weekly pass actually decreased from $18 to $15 to better align with the $59 monthly pass cost. "[MBTA General Manager] Grabauskas said weekly pass buyers often have trouble paying the up-front price of a monthly pass...The change takes away the penalty of buying weekly passes." (Source: Boston Globe, October 7, 2006)

Figure 7-5 All MBTA riders who would have gotten better value from purchasing a weekly pass



regardless of which group they were in, would have received better value by buying a pass product. A reminder that ordinary smart card users (the control group) could purchase a weekly pass or a monthly pass, but limitations with the MBTA's existing Automatic Fare Collection system restricted those in the treatment group from buying a weekly pass, so the only option for them was a monthly pass or pay per ride. (The discounted monthly pass was $30, a 65% discount over the ordinary pass price of $84.50.) For each control group participant paying with cash balance, a rolling 7-day total expenditure was calculated. 30% of these participants had at least one window, over the course of the study, where it would have been financially beneficial to have purchased a weekly pass. In a similar fashion, for each treatment group participant paying with cash balance, a 30-day total expenditure by calendar month was calculated. Similarly, 30% of the treatment group participants would have benefited financially from having purchased a discounted $30 monthly pass at least once. The same percentage held true for both control and treatment groups even though the pass types differed.

Figure 7-6 Study participants who would have obtained better value from purchasing a pass

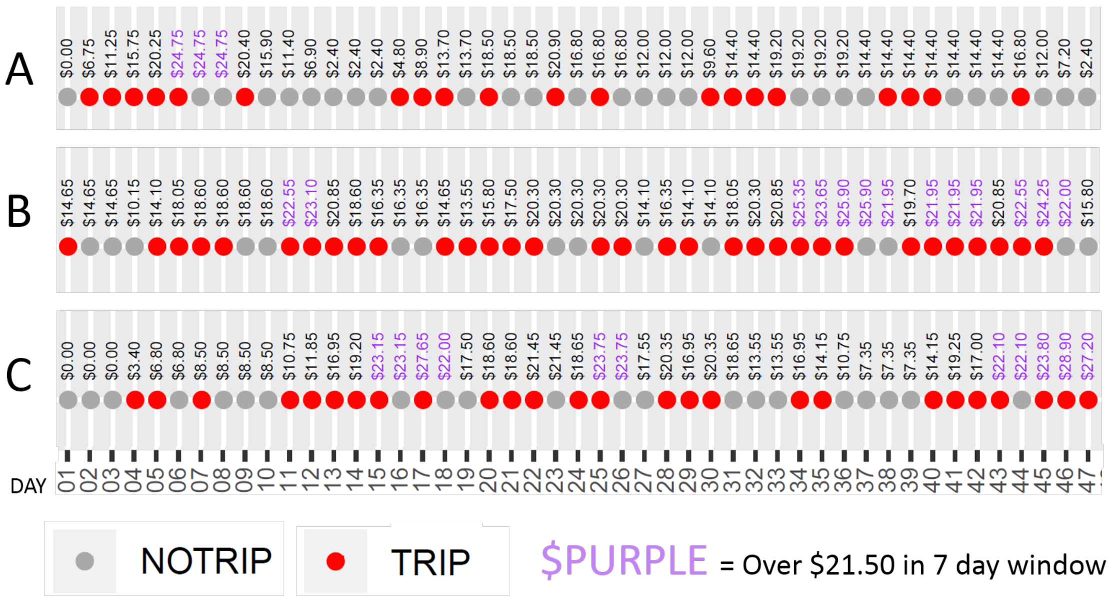


To illustrate, Figure 7-7 presents sample smart card travel records for three participants who were paying on a per-trip basis. Each dot represents a single day and is colored red if any trips were recorded for that day and grey if not. The dollar amounts indicate the 7-day rolling sum of payments ending on that day– when the value exceeds the equivalent weekly pass value of $21.25, the amount is shown in purple. Participant A once surpassed the weekly pass value after 5 days paying $3.25 extra. Participants B and C went over several times during the period presented by as much as $7.40.

Another interesting finding is that none of the study participants who surpassed the weekly pass value at any time ever used a pass product during the course of the study. Meaning, inversely, none of the participants who alternated between pass product and per trip payments ever surpassed the weekly pass value when paying on a per trip basis. The next section includes a discussion of this finding in the context of behavioral science theories.

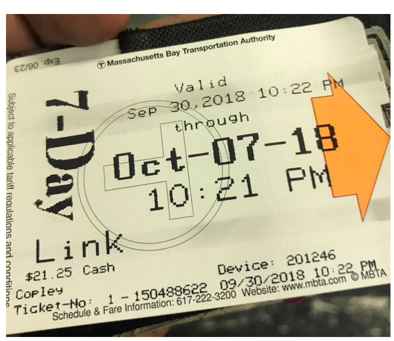
Looking across all MBTA riders who purchase a weekly pass, 65% are put onto a plastic CharlieCard and 35% on paper CharlieTickets. During the interviews, some participants explained their preference for the paper CharlieTicket because they have precise expiration date/times printed on them (Figure 7-8) which serves as a helpful reminder when the pass

Figure 7-7 Example travel records and 7-day rolling-sum of single-pay riders in the Control Group



will expire. One participant indicated that seeing the pass information written on the CharlieTicket provided a level of comfort and security that the pass actually exists on the fare media. Not trusting the electronic payment system, he expressed comfort in having the pass printed on the ticket if he was ever confronted by the Transit Police.

Figure 7-8 Weekly CharlieTicket image



7.2.2 Short fares/ fare evasion

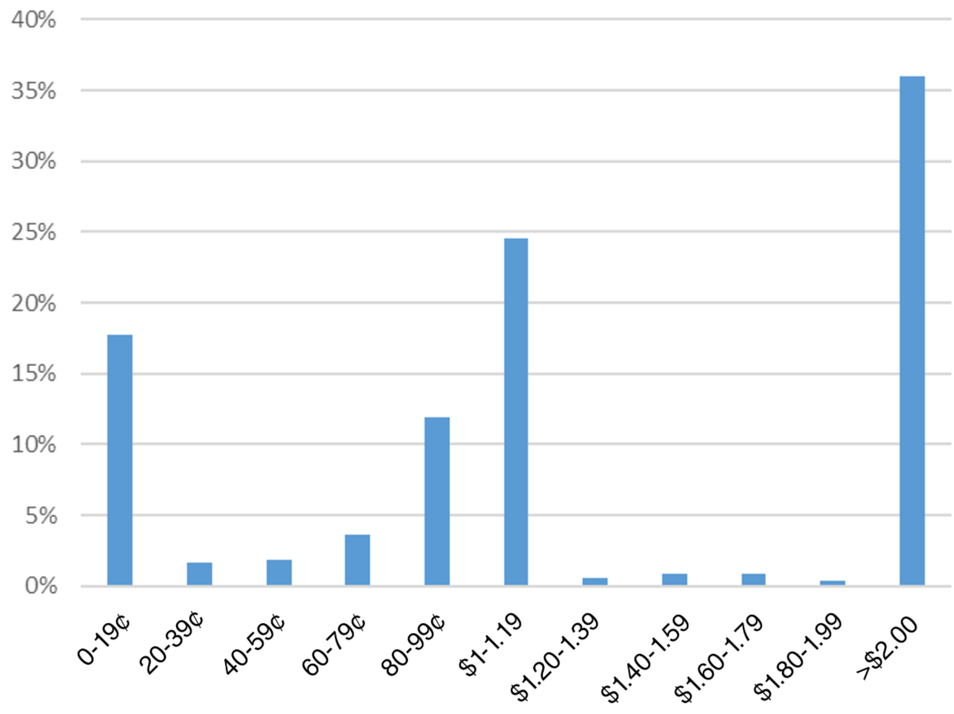
I first present an analysis of underpayment patterns on MBTA buses. This could be considered a form of fare evasion, though interviewees indicate that informal approval for such behavior is given by bus drivers. The impetus for doing this analysis originally came from an observation I had a few years ago while riding the bus. Two men who appeared mildly intoxicated attempted to board the bus and not pay. The driver, in essence, said, "Oh no, don't think you can get on my bus without paying. Come on, at least put something in there." They did not, and she insisted they exit the bus which they did. I took away from that experience the hypothesis that there might be a informal policy among bus drivers to accept less than the full fare, an expression of the *street-level bureaucrat* phenomenon.[26] This observation is related to a previously noted finding that there is a higher number of cash transactions than would be expected given the the 50¢ cash surcharge. By paying cash, riders are able to pay less than the required fare.

The way the automated fare collection system works, if someone begins paying with cash, the farebox displays a running count of the amount of money inserted. If someone has not put in enough, the farebox in essence does not register the transaction. The only way to ready it for the next customer is for the driver to push the *short* button. Therefore, within the fare collection system database, I have access to the number of short transactions and the amount of underpayment for each. Overall for 2017, 55% of all cash transactions on the MBTA buses were underpayments, and about $5-6\%$ of all bus transactions are cash. Figure 7-9 shows a histogram of cash payments on all MBTA local buses for 2017. About 35% paid the full fare (note that cash fares are $2.00 while CharlieCard fares are $1.70). 20% pay almost nothing and 35% pay close to a dollar. This analysis serves as additional evidence

[26] Street-level bureaucrats are "public service workers who interact directly with citizens in the course of their jobs, and who have substantial discretion in the execution of their work" (Lipsky, 1980).

that transit affordability is an issue. Note that this analysis does not include fare evasion, which is not recorded through the AFC system.

Figure 7-9 Histogram of cash payments on MBTA buses 2017



Personal pride and fear of embarrassment plays a role for some individuals. The following comes from one of the interviewees. "When I got on the bus, 'Oh my gosh,' I said to the driver, I'm so sorry, I switched jackets and and my pass [was in it]. The bus was packed like sardines, it was rush hour. And I had never ever done that. And I can understand from time to time you get people try to get on, I've seen it. And I said, 'well, I'm telling the truth.' I said, 'you don't have to embarrass me like this in front of people,' I was so humiliated. Ever since that time, I just made sure. Like one time I walked from Forest Hills to Hyde Park because I didn't have the extra money [for the transfer]. And once I walked from here [Dudley] all the way to Roslindale."

For others, though, behavior is in the form of abuse toward the driver. One participant made the following observation, “I’ve seen a pregnant lady and her child’s father literally curse out the bus driver because they just walked on and went to the back and he said a ‘I’m waiting for the fare’ and they literally used profanity and stayed on the bus until they got to their stop. It happens a lot.” Another person I interviewed conveyed a similar story, “a young man got on and showed some kind of pass that didn’t work. The driver said that’s not real. [The man said] ‘It’s a weekly pass,’ but it was really some old pass. He walked to the back of the bus and starts swearing at the driver. And the driver refused to move the bus and said, ‘there’s no reason for you to swear at me, I didn’t do anything to you.’ And [the man] stood there on the phone swearing and the bus driver refused to move. So finally he got off the bus and hucked and spit right on the windshield of the bus.”

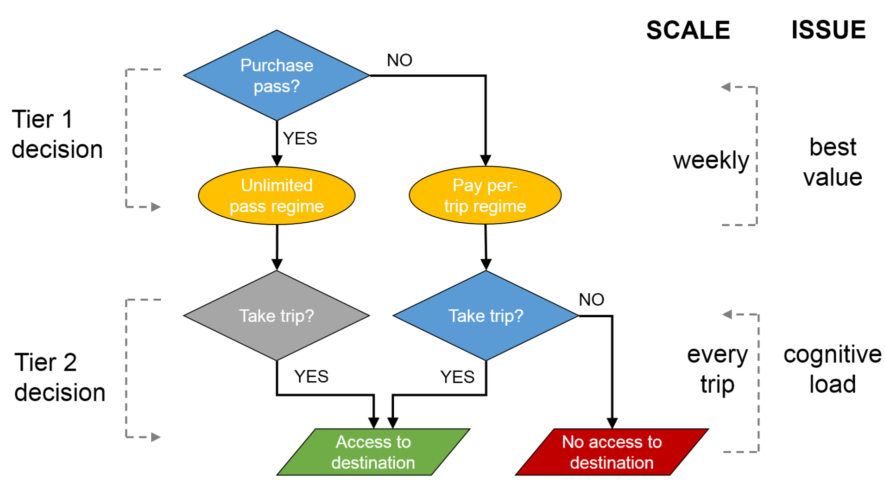
Here is a description of another type of rider as told by one of the interviewees, “You have the ones that you can see that they have an issue, alcohol or drugs, or just something else. And they come on and say oh they don’t have [the fare]. And the bus drivers just let them on. Sometimes I see them say something to the driver and then they put in $1 or whatever they had like $1.20 or whatever.”

7.3 Decision making

7.3.1 Two-tier decision model

This section provides additional context and depth to what is often considered a more simplistic issue of transit affordability as a barrier to accessing desired services and activities. Whether low-income individuals pay for transit using a purchased unlimited pass product or choose to pay per-trip on a pre-paid cash balance smart card has an important impact on travel behavior. Once the pass purchase decision is made, there are no subsequent per-trip affordability decisions to make when traveling, but without the pass there are affordability decisions necessary for each potential trip. I represent this two-tier decision-making model in Figure 7-10. The decisions made in each tier have important financial and accessibility implications for low-income transit riders. The first tier decision is whether or not to purchase a weekly pass, which has implications for getting the best value out of expenditures on MBTA trips for a particular week.[27] As 30% of participants would have benefited economically had they purchased a weekly pass, it is important to better understand how and under what conditions these decisions are made. Using behavioral science insights to guide the participant interviews, I set out to make sense of this apparent disconnect.

Figure 7-10 Two-tier decision model



Conventional wisdom, as conceptualized by the economic *rational man*, suggests that an individual will choose the option that makes the best economic sense.[28] It turns out that this is frequently not the case. The analysis in the previous section indicated that 30% of low-income individuals choose not to get a pass when it would have been in their overall

[27] While a weekly or monthly pass product is available, this section focuses on the weekly pass product because, as mentioned in the last section, purchasing four weekly passes in essence amounts to the same cost as purchasing a monthly pass, but in installments.

[28] Economics traditionally conceptualises a world populated by calculating, unemotional maximisers that have been dubbed *homo economicus*. In a sense, neo-classical economics has defined itself explicitly as 'anti-behavioural' by ignoring or ruling out all the behaviour studied by cognitive and social psychologists (Smits, 2006).

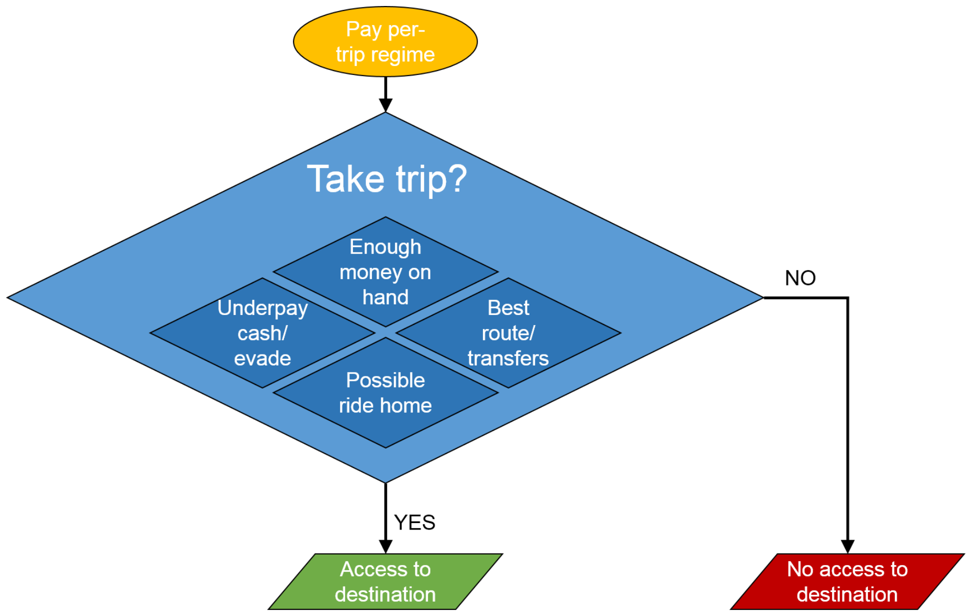
best financial interest to do so. This behavior occurs at a much greater frequency than I had expected, surprising because one would think that financially constrained individuals would be more apt to utilize cost-saving measures.

The second tier decision is whether or not to take a given trip each time one is considered. Those decisions only have to be made when paying on a per-trip basis. There are several implications to consider. Operating within a pay-per-trip regime requires individuals to make decisions, often on the fly, about whether to take trips. Conducting a cost and benefit analysis for every potential trip adds to cognitive load. This, according to behavioral science theories, leads to a scarcity mindset which in turn hinders good decision making. Considering this decision making process in more detail, there are several sub-decisions often considered, adding even more complexity. Figure 7-11 identifies the ones that commonly surfaced during the participant interviews: having enough money on hand or on a smart card, considering fare evasion, or underpaying with cash on the bus, planning trip routing and activity coordination to maximize value from transfers, and factoring in the possibility of getting rides later in the day.

This describes a type of *cliff effect*: Once the decision has been made to purchase a weekly or monthly pass, subsequent individual decisions to take transit trips would no longer be based on affordability– travel that week is unencumbered by the factor of cost. This situation is binary in nature with no middle ground. When paying for each trip one at a time, participants reported evaluating the importance of each trip and needing to make constant tradeoffs in the moment. Not surprisingly, the interviews revealed that forgoing transit trips occurred when paying per-trip. Based on the *scarcity mindset* theory, the added cognitive burden leads to increased stress and hampered executive function.

A consistent theme emerged from the interviews: stress and anxiety results when individuals must pay for trips one at time. Recognizing this behavior, it is even more surprising that

Figure 7-11 Decision making issues for individual trips



the stress-reducing benefits of having the weekly pass does not appear to play a stronger role in the decision making process. From that perspective, the overall value of the pass should be greater than the monetary cost because of the added psychological value of not having to think about each trip.

7.3.2 Behavioral archetypes

The interviews provided a better understanding of how the observed behaviors described in the previous section play out in the decision making process of individuals. I found that participants fall into one or the other of the following two categories: attentive decision planners and inattentive decision planners. Some were very careful about planning ahead for the upcoming week's transportation needs and made pass purchasing decisions accordingly–what I call the *attentive planner* archetype. The *inattentive planner* archetype, on the other hand, did not articulate an organized thought process. Instead, they reported either buying a weekly pass out of habit or spending per-trip without much consideration of buying a pass.

These findings support the idea that some individuals exhibit behaviors consistent with the scarcity mindset model in the context of paying for transit. I describe these two archetypes and provide supporting evidence from both the smart card data and interviews.

✻ ✻ ✻

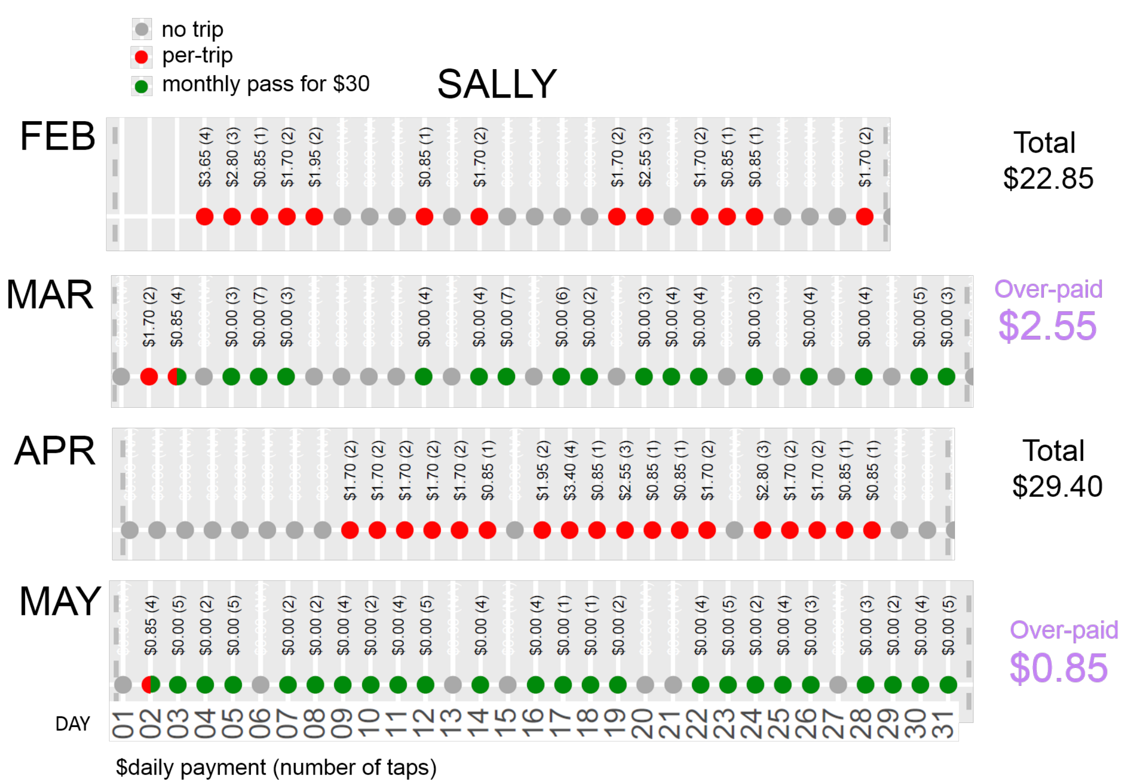
“Attentive” archetype

Carice represents an example of an *attentive planner*. She describes her thought process: “so I used to get the weekly pass when I was working. Now, I have to eliminate the weekly pass. I have to look at the calendar, study the calendar and study my appointments and the errands I have to run to decide is it worth it to buy a weekly pass. So now I just use the Charliecard and just pay because it comes out cheaper right now.” She is aware of the tradeoffs and makes the decision according to overall cost.

Sally is also someone who falls into the “attentive” category. When asked how she decides whether to buy a weekly pass or not she said, “that’s what I do. I sit down and I study the calendar, see what I have to do each week, and if I see that it’s not worth it to pay as I go.” Here, she is exhibiting many features of executive function from Table 7.1 such as task initiation (ensuring she takes the time at the beginning of the week to make a decision), planning (reviewing the activities for the week and determining the transit trips required), and organization (keeping an accurate calendar). I asked if she ever ended up overpaying by paying for rides individually. “It has happened to me a couple times in the past I have paid as I went and it turned out to be more expensive than if I had gotten the pass.” This demonstrates working memory (drawing on past experiences), organization (keeping track of how much was spent), metacognition (reflection on how she is doing with her goal of financial optimization).

In analyzing Sally's smart card data, I found her behavior during the study to match how she described herself during the interview. As she was in the treatment group, she had the choice of either paying per ride at half-price or purchasing a monthly pass for $30. Her usage data for four months is presented in Figure 7-12. For February and April, she only paid on a per-trip basis and did not exceed the $30 threshold. For March and May, she purchased the monthly pass within the first few days of the month, paying on a per-trip basis a few times initially. Minimal over payment occurred. When asked about this during the interview, she indicated that there is not a fare vending machine or retail sales location close to her house. A bus ride is first necessary to reach a subway station in order to purchase the pass. Looking at her records for April, she took one bus ride for $0.85 and then purchased the monthly pass.

Figure 7-12 Details of Sally's smart card data



Tom is another attentive planner. He describes his thought process as follows: "my schedule is usually set for the week at the beginning of the week. So I'll know whether I need just a day somewhere or if I know I'm going to go enough places during the week, I'll get a weekly. So it all depends. Like this weekend, I know I'll end up buying a weekly pass that will carry me into next weekend. Because I'm spending time with my son and he wants to do the Constitution, and trying to decide between the Museum of Science and the Wax Museum downtown because he's never done that before. So that's going to be lots of trips right there." I asked if he ever got a monthly pass. "Rarely. The summertime I do because I see my son a lot more over the summer." Tom was in the treatment group. Looking at his smart card data, he used the MBTA infrequently during the study period and when he did he always paid for each trip individually. The most he spent in any month was $15.20 so not much can learned from this datapoint.

* * *

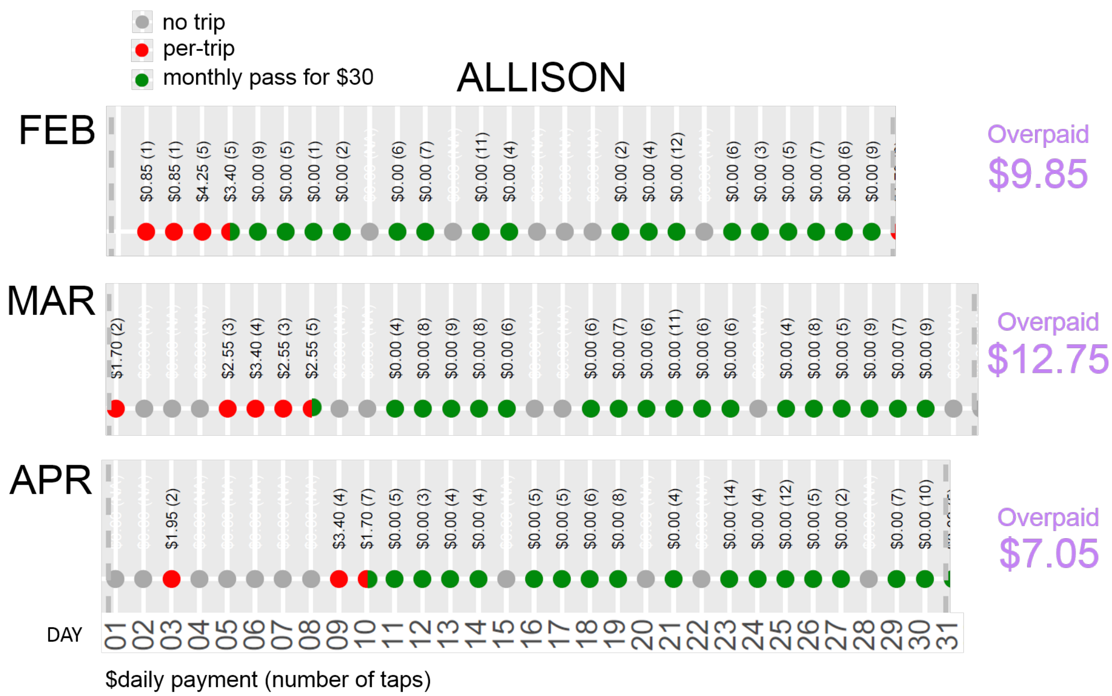
"Inattentive" archetype

Allison has so many things going on, she says she has difficulty keeping her life in order. She indicated the highest level of stress from the two stress questions asked on the study's intake survey which corresponds with her description of herself. She tries hard to be on time for doctor appointments but regularly gets behind schedule and either arrives late for the appointment and has to reschedule or skips the appointment altogether once she knows she will be late. "I was never like this as a kid," she offered in an apologetic tone of voice during the interview. From this, I infer that her current scattered state of mind is not a personality characteristic, but caused by her current life circumstance.

When discussing her choice to purchase a pass or pay-per-ride, she indicated, "sometimes I know I should get the weekly, but I'm just not paying attention and forget to get one at the station, or I get [to the fare machine] and then realize I don't have the $20 something in cash on me so just load a few dollars. Then a few days go by, and I think maybe I didn't spend enough to make it worth it." At one point she recollected, "sometimes I'll be on the bus and all of a sudden think to myself, 'I bet I should have gotten a weekly pass,' but I'm never really sure." I asked her to talk through the next week and explain how she would decide whether to get a pass, and she had difficulty remembering what things were on what day, kept going to her phone to check email and texts, becoming more agitated and nervous as she continued describing all the things she had to take care of. By the end of the process, she had forgotten that the purpose of the exercise was, in the end, to determine whether she should get a weekly pass, though at that point I shifted the conversation to something less stressful. This evidence suggests that something is affecting her executive function.

Later during the interview with Allison, I asked her to think back during the study period when she had the discount CharlieCard. How did she decide then whether to get the monthly pass or not? "Oh, yea, for $30 I knew that was a good deal, so I really tried to get my pass first thing. I think for one of the months I had to borrow to get up to $30, but I had to do it." I asked if she did the calculation of how much it would cost if she paid for each trip individually at half price each. After thinking for a few seconds, she said, "I guess I didn't really think about it, I just assumed that $30 was so much better than $84.50," which was the cost of the non-discounted monthly pass. In reviewing her CharlieCard data, I found that she did indeed purchase a monthly pass each month, but did not manage to do so at the start of the month, as shown in Figure 7-13. This meant she was overpaying, in that if she had purchased the pass on the first of the month, it would have been valid for the days when she paid per trip. This cost her between $7 and $13 per month, which is equivalent to a 25% to 45% additional charge. When I asked her about having several days go by before buying the monthly pass during the study, she said, "really? I don't remember that. I thought I got it on like the second or third day or something."

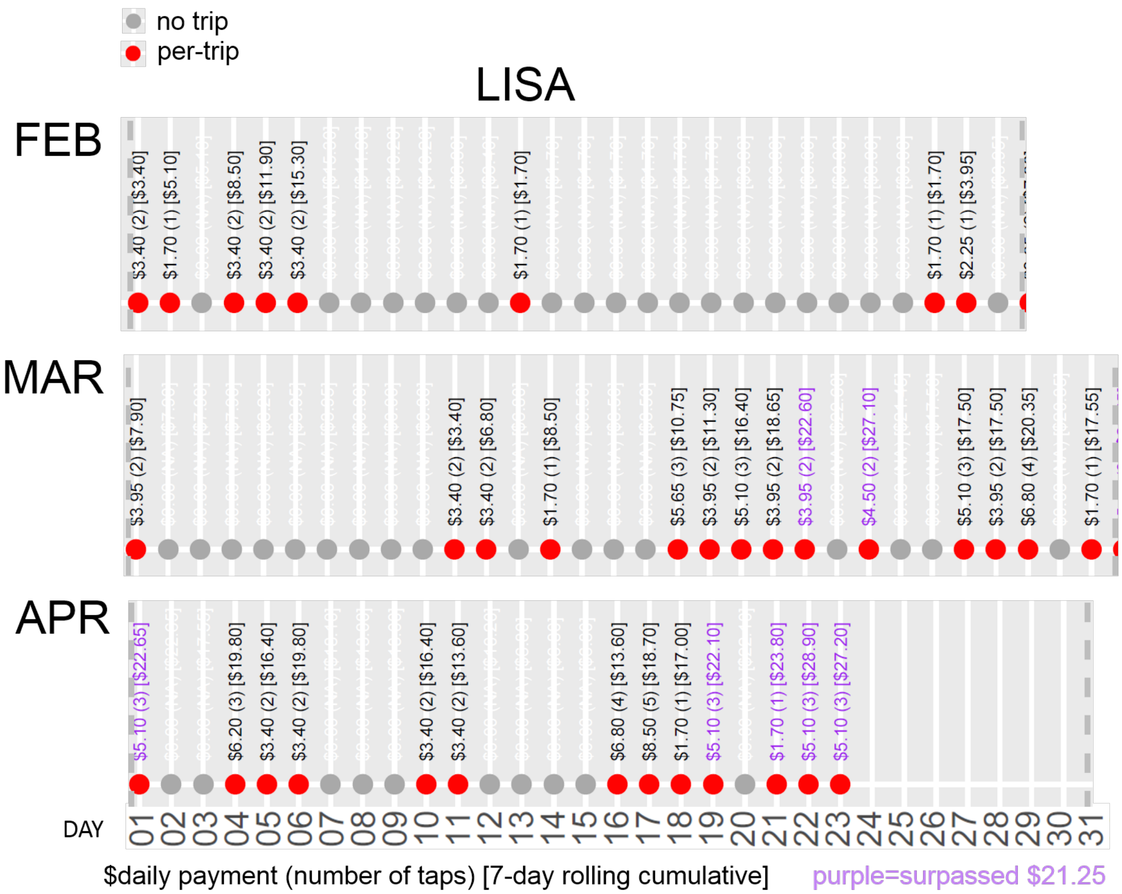
Figure 7-13 Details of Allison's smart card data



Lisa is another study participant who exhibited *inattentive* behavior with respect to purchasing a pass. In describing how she budgets for transportation, she said that for transit she sets aside money ahead of time. "$20 will get me through the month because I don't ride every day. What is it now like $60 for the monthly pass? The last time I got a combo pass was it was like $60. So that's been a while. Because I don't travel like that." I asked about whether she got the weekly pass, and she indicated yes, she sometimes does. "It depends on what's going on that week. If I have to go to my mother's more than twice, yea I guess I got that right, more than twice within that week, then I'll get [the weekly pass]." I followed that up to confirm that she would get the weekly pass if she had at least four 1-way trips. Again, at $1.70 per trip, that's only $6.80, far lower than the threshold of $21.25 for the weekly. With a weekly pass costing $21.25, this response did not reconcile with her earlier statement that she only spends $20 per week.

Lisa's self-described travel behavior was not reflected in her smart card records for the time during the study. As a control group participant, I analyzed her per-trip payments to see if there were any times where a weekly pass would have been prudent. The data in Figure 7-14 is delineated by month, but when considering the value of the weekly pass (which is valid starting on any day it is first used), monthly markers are irrelevant. Looking at Lisa's payment patterns, there were several periods over the course of the approximately 85 days in which she used the study card when she would have benefited from purchasing a weekly pass (shown in purple). When I showed her this data later in the conversation, she lit up in surprise. "I would have never guessed. Wow I spend more on transit than I think. I wish there was an app or something that could tell me how much I've spent, that would help cause I really can't keep track of things."

Figure 7-14 Details of Lisa's smart card data



* * *

From "inattentive" to "attentive"

Before jumping to the conclusion that individuals' archetypes are determined by some innate personality characteristic, I found evidence of a participant who shifted from one mode to another. Anthony used to always pay for trips one at a time and never went through the process of considering whether the weekly pass would be a better option, as illustrated by this quote:

> "I always did that [did not purchase a pass] until I sat down with more educated T-riders. Now I got it down pat and I'm one of the ones who can sit down

with somebody and even tell him when I see him getting the paper ticket thing, but then I go no no no, you're gonna kill yourself with that. If you got some money, get a weekly or monthly, but if not, you at least want [to get] yourself a hard card to save money. Because if I had five days a week to work, and that week, I had three unscheduled things that had to be done besides work. I'd be almost at $45 $50 that week and if I had a weekly $25, now I can help people do that thinking. Huh, just talking about it makes me think back, how I used to not think about the pass and just one ride at a time, how could I have been that way?"

7.4 Policy implications

Next generation fare collection systems. Next-generation fare collection systems will have far more flexibility than the ones implemented a decade ago in the mid 2000's. Chicago implemented Ventra in 2013, the first open fare contactless card payment system in North America, and new systems are currently planned for New York City and Boston.[29] There are two key developments with the new systems: they are designed as account based systems rather than card-based systems, and they are "open fare" systems which accept other payment forms such as credit and debit cards. With current systems such as the MBTA's CharlieCard system, all the necessary information, such as cash balance, product type and expiration, and last validation, are stored on the smart card (or magnetic stripe ticket) itself such that the fare collection systems can operate without a direct internet connection to a centralized system. The fare vending machines and fare gates in stations periodically synchronize with the main system. Bus fareboxes only connect when done so manually at the depot. Advances in telecommunications technology have allowed newer systems to constantly be centrally connected. 4G technology will improve the reliability and speed of these connections dramatically. Under the new regime, the smart card itself only serves as an

[29] For an overview of the proposed Boston system as of April 2019, see https://www.mass.gov/files/documents/2019/05/06/dot_glx_AFC_2-0_overview_20190402.pdf

account identifier. Credit or debit cards and smartphone payment methods could also be connected to a user's "account" to identify them in lieu of a transit agency issued smart card. Because the system is always online, credit and debit cards could also be used without any preregistration– users can just tap and go. This "open fare" system eliminates the need to interact with fare vending machines, thereby significantly reducing the friction inherent in using older systems.

The new systems afford a number of opportunities. They provide real-time access to usage and balance information, so users could check their balance on their smartphone at any time. The interviews I conducted suggest that this would significant benefit low-income riders. Furthermore, the newer systems will offer transit agencies additional flexibility in designing fare policies. It is challenging to add different fare products to current systems. Newer systems will allow for more flexibility in implementing low-income fares, time of day fares, and other innovative fare products. The current system is only able to handle a low-income fare discount similar to what is provided to seniors and persons with disabilities.

Another key benefit is that next-generation account based systems allow far more flexibility for administration. For example, I have been pushing the idea of embedding a CharlieCard chip inside all newly issued MassHealth and food stamps (SNAP) cards. But there is currently no easy way to turn on and off, or otherwise modify, fare products associated with a particular card because that information is hardwired onto the card. The only thing the MBTA can do now is set the system to deactivate a user's card the next time it interacts with a farebox. Once deactivated, a card cannot be reactivated. This functional limitation significantly hinders innovative programs. For example, a discounted smart card assigned to a food stamps beneficiary could not be turned on and off depending on their current benefit status. Next generation systems, on the other hand, could integrate with existing social service programs such as MassHealth and SNAP thereby reducing the administrative overhead.

Additionally, social service programs that want to provide free or discounted transit to their clients could do so much more seamlessly. When interviewing the head of policy for Boston's Workforce Development Office, I discovered that several nonprofits purchase CharlieTickets containing $21.25 value, the equivalent of a weekly pass, but in the form of a cash balance. The client then needs to go to Downtown Crossing station to the only available customer service center to turn funds into a weekly pass. This high burden highlighting just one limitation of the existing system. A new system would permit these transactions to happen online with funds easily transferred from one agency to the MBTA.

Fare capping. The concept of "fare capping" has garnered attention since the advancement of fare media technology in the 2000's made such a scheme possible. Fare capping is designed such that the transit rider pays for each trip individually with a specified smart card (or other account-based system), but when payments reach a level equivalent the cost of a pass product, the system stops charging the user, in essence "capping" the total cost over the course of a payment period, such as a month. This removes any risk to the user associated with deciding ahead of time whether to purchase an unlimited pass. However, this is potentially costly for transit agencies, such as the MBTA which currently sells a significant number of monthly passes, especially through its corporate program, that are greatly underutilized (see Figure 7-4 on page 188). Transport for London implemented fare capping in 2005 for the "Oyster" smart card on a single-day basis (Streeting & Phil, 2006), which eliminated the possibility someone would pay more for their daily travel than if they purchased a 1-day pass.

From a strictly financial perspective, a weekly or monthly fare capping system would be advantageous to low-income individuals because it would remove the first tier decision making element and shield them from overpaying. The findings presented earlier in this chapter indicate that it would provide concrete savings to a significant number of low-income riders. From a behavioral science point of view, though, second tier decision making, done on a trip-by-trip basis, may not see a direct benefit. If individuals continue to consider the possibility of spending less than the cap, they will continue to experience stress over individual trip making choices. These individuals will not receive the psychological benefit of having a pass product which frees them from the individual trip decision making burden. Evidence from the study, that treatment group participants did not purchase monthly passes at higher rates, suggests that for many, the *hope for savings* mentality persists even with fare discounts, hence, accessibility will still be affected. Herein lies a policy dilemma. If the agency implements fare capping, considering the purchase of a pass product becomes irrelevant so everyone will always pay on a per-trip basis. The agency could, though, provide a discounted weekly pass for low-income riders and not offer half price individual fares as a way to incentivize pass purchasing. To the best of my knowledge, this concept has not been discussed.

Cashfree buses and proof of payment. Several agencies, including the MBTA, are using the shift to new fare collection systems to change some of the existing parameters of payment. The first is removing the cash payment option on buses. This creates a challenge for low-income riders who are unbanked, but based on the participant interviews, many who are considered unbanked use prepaid debit cards which would be accepted on new systems. To many advocates, the fees associated with these products are exorbitant and, as such, are wary of supporting a system that pushes individuals to use such products. In the retail arena, advocates in the US are pushing for laws that prevent stores from rejecting payments in cash.[30] Yet many I interviewed preferred using those products instead of banks and did not mention problems with the fees.

[30] The Cashless Retailers Prohibition Act of 2018 is a bill that would prohibit retailers from not accepting cash or charging different prices depending on the form of payment used. The bill claims that cashless businesses effectively discriminate against people with low incomes.https://www.kittelson.com/ideas/the-benefits-and-drawbacks-of-a-cashless-public-transit-system/

Many interviewees, however, revealed they are distrustful of institutions like the MBTA, and skeptical of any technology involving banking and money. This suggests it will challenging to meet the needs of those who insist on using cash to load their card. In order to provide the option to add cash to a smart card, the new systems would require the placement of a significant number of off-board kiosks, an incredible challenge for a system like the MBTA with a vast bus network. The initial contract for the new fare collection system included performance standards to guide the contractor rather than the agency determining the specific locations for the machines. The contract is being renegotiated and this component will be removed such that the MBTA will now make all placement decisions. Under either mechanism, access to locations to add cash to smart cards is a highly contested element of the new fare collection system. To help ameliorate the situation, the MBTA plans to permit the new system to allow for a negative balance such that someone without enough balance could board the bus with the expectation that they would pass by a core MBTA station or kiosk later that day. Though that makes sense conceptually, users will just consider the negative balance potential as a free ride and not keep it available for emergencies, negating its intent.

Nudge. Much of the discussion about reducing the cost barrier to low-income individuals revolves around providing fare subsidies. But another potential policy intervention involves nudging low-income riders in such a way as to improve their accessibility and use of transit. One mechanism is to identify ways to enable riders to choose the weekly pass option when appropriate. From the interviews, I found that the lack of a feedback mechanism on travel behavior and pass usage reduced individuals' abilities to reflect back on their prior actions to make corrections for the future, so providing this information would enable more informed decision making. This is not to suggest that discounted fares for low-income riders are not an appropriate policy intervention to improve accessibility to the city. But it highlights the important role that behavioral science, together with appropriate financial instruments, can play in the development of fare policies. Even in the context of big problems, small factors can play a decisive role in improving the lives of low-income individuals.

8

Conclusion

The findings presented in this dissertation contribute to the limited body of knowledge that currently exists regarding how those at the lower end of the income spectrum use public transportation. In particular, the research focused on affordability of the fare. Interest in means-tested public transit fare programs has grown rapidly over the past few years, yet scant research exists to help policy makers and politicians assess the potential value of such programs and rank them against other competing policy demands. Academics have limited understanding of the extent to which today's transit fare levels act as a barrier to low-income riders, and, if so, what types of destinations are more likely to be affected. Health literature points to the importance of transportation for accessing regular healthcare visits for chronic illness, but has not conclusively identified the cost of public transit as a cause of missed appointments. Little is known about how low-income individuals choose to pay for transit, and what the resulting impacts are on individual trip-making decisions.

To investigate these issues, I took a mixed-methods research approach combining a quantitative experiment with qualitative interviews. I designed and implemented a randomized controlled evaluation to test the impact of discounted transit fares on travel behavior of

242 low-income individuals who receive food subsidy benefits in the Boston area. Half were provided a discount smart card while the other half were provided a standard one. An automated ChatBot texting tool was developed to administer a daily travel diary which collected trip purpose information from the study participants. Following the quantitative study, I conducted semi-structured interviews with a subset of 20 participants to gain insight into decision making regarding access to healthcare and transit payment methods. The latest MBTA ridership survey and US Census microdata were analyzed to provide additional context and insights.

8.1 Findings and implications

The research questions and findings are summarized in Table 8.1 and discussed below.

Table 8.1 Research questions and a summary of findings

Research questions	Methods	Summary of findings
1. How do travel patterns of low-income transit riders differ from those of average riders?	Descriptive statistics	Low-income riders take proportionally more off-peak trips. African Americans have longer commutes even controlling for income.
2. What is the causal effect of a fare subsidy on the number of trips taken by low-income riders?	Randomized controlled evaluation	50% fare subsidies cause an increase of 2.3 trips per week (27%), equivalent to a fare elasticity of -0.54. There is a statistically significant increase in trip rates to healthcare destinations.
3. In what way does transit cost impact healthcare utilization for low-income individuals?	Semi-structured interviews	Healthcare trips for chronic conditions are the type likely to be forgone.
4. How do low-income transit riders decide whether to purchase a pass or pay for trips individually?	Semi-structured interviews	*Scarcity mindset* theory is not universal among low-income individuals. 30% of individuals paying for trips individually would have received better value by purchasing a pass product.

* * *

(1) Low-income transit riders take more off-peak trips, utilize transfers twice as frequently, and are more likely to live in a zero-car household. African Americans have longer commutes by all modes even controlling for income.

Comparing the smartcard records from participants in the study with those for overall MBTA ridership, I was able to distinguish time of day travel patterns, finding that low-income transit riders as a group take proportionally fewer transit trips during peak hour than the average rider. These results address a particular concern of the MBTA that the increase in ridership induced by a means-tested program would exacerbate peak hour crowding on the system. This illustrates the paradox of competing policy objectives for public transit systems that rely on public subsidy to operate: the desire to serve more people, be equitable and just, and at the same time minimize costs. The marginal cost of serving additional passengers during off-peak is minimal because these passengers can be accommodated using existing vehicles. Additional riders during peak hours, though, requires additional service which costs more than the increase in fare revenue, especially if those riders are only paying half-price fare. It is perverse, though, that transit agencies argue that increasing ridership would be a reason not to implement an important public policy initiative to further equity and justice objectives. Some advocates argue that overcrowding is necessary to build the political support for more funding (Schumaker, 1975).

26% of trips by low-income riders involve a transfer, which is twice that of the average population. Three hypotheses exist for this finding: (1) They live further from rapid transit stops so local buses are used as a *first-mile* feeder service to rapid transit or other core bus service, (2) Their destinations are not directly served by one transit line, or (3) They design their journeys such that they are actually taking two unique trips but pay for the second one by utilizing a transfer. There was some evidence of all of these behaviors in the interviews. 60% of low-income riders live in a zero-car household, which is about three times that of other riders. Low-income riders without a vehicle will rely on transit for more trips than middle class riders, (use transit primarily to commute), reinforcing the need for affordable transit service.

Finally, analysis of US Census micro-data indicates that African American transit riders have longer commutes than white transit riders regardless of income. I found this to be true for bus, rapid transit, and driving commute trips. This confirms the findings reported in a similar analysis which neglected to control for income (Pollack, 2012). Given that there is a higher percentage of lower-income African American Bostonians than whites, it was important to verify that the correlation with commute time was based on race and not on income. It was important to confirm Pollack's finding given how frequently it has been used in public discourse. It contributes additional evidence that the racist structures put in place decades ago still manifest today.

* * *

(2) Fare subsidies have a causal effect on travel behavior.

Participants in the control group took on average 8.5 trips per week while those in the treatment group took on average 10.8 trips per week, a treatment effect of +2.3 trips per week (a 27% difference). The elasticity of demand is −0.54. The results were statistically significant at the 95% confidence level. Even if the treatment effect was +0.5 trips per week, the lower bound of the confidence interval, it would still indicate a meaningful increase. This evidence indicates that the current cost of transit fares in the Boston area does limit the number of transit trips taken by low-income riders. The implication is that a means-tested fare program would increase the use of transit by low-income individuals and, based on the literature, lead to better outcomes for the individuals served.

This research makes an important contribution to the policy making discussion because it resolves the previously unanswered question regarding whether discounted fares will increase ridership. There are two conflicting narratives in the literature regarding fare elasticity of low-income segments of the population. One suggests that, being captive transit riders because of the lack of car ownership, they will continue the same level of consumption because they lack alternatives, instead shifting funds away from other household expenditures. Alternatively, they might be less tolerant of the effects of a fare increase as it represents a greater proportion of their already constrained household budget, thus leading to a reduction in number of trips taken. The findings presented in this dissertation point to the latter. These findings do not negate the influence of other factors such as the quality of the service provided, but indicate that transit cost is an important factor.

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(3) Transit affordability impacts access to healthcare, and appointments for chronic conditions are more likely to be forgone.

Findings from the travel diary indicate that there is a statistically significant difference of about 2 healthcare trips per month on average between the treatment and control groups. Because many participants reported zero healthcare trips, the calculation was made in two ways: including the zeros and excluding the zeros. In both cases, there was a statistically significant difference. The participant interviews suggested there is evidence that healthcare trips for chronic conditions that require regular maintenance visits are the types of trips forgone, and participants reported transportation affordability as a contributing factor. None of the respondents reported cost as a factor affecting emergency visits or doctor visits for acute illnesses. A contribution of this research is the incorporation of an accessibility measurement.

These conclusions augment the call by many for better systematic integration between healthcare and transportation accessibility. Given the extensive literature on the negative health impacts associated with low-income individuals missing appointments for chronic illnesses, one would expect much more attention to the transportation access component of healthcare. In addition, there are significant healthcare costs associated with individuals who do not properly manage chronic conditions. From a purely cost-benefit perspective, it seems the gains in public health would vastly outweigh the relatively small cost of providing free (or discounted) public transit to healthcare appointments. One of the features of the Affordable Care Act encourages the creation of *Accountable Care Organizations* (ACOs) which aligns economic incentives with the combined objectives of controlling health care costs, upgrading quality of care, and improving overall population health. Instead of being paid through a reimbursement for services, these organizations are provided designated fixed benchmark funding for a designated population of individuals. Spending under that threshold allows the ACO to obtain a portion of the cost savings (McWilliams, Hatfield, Chernew, Landon, & Schwartz, 2016). This creates an incentive to address the needs of the target population proactively, rather than reactively, and in a more holistic manner. As these institutions continue to form around the US, one would expect a greater focus on mobility as enabling improved patient outcomes. A review of existing ACOs found that the nonmedical needs most commonly addressed were transportation, and housing and food insecurity, but the potentially differing transportation needs of urban and suburban/rural residents were not identified (Fraze, Lewis, Rodriguez, & Fisher, 2016).

Massachusetts, through MassHealth which administers both Medicaid and the Children's Health Insurance Program, does provide paratransit service through the *Prescription for Transportation* program, but individuals who can travel to appointments by public transit are technically not eligible. Although there is a component that offers reimbursements for transit use, it is poorly marketed and cumbersome to utilize. With MassHealth's paratransit service costing approximately $25 per ride, it is surprising that MassHeath administrators do appear to recognize potential cost savings by using discounted or free fares to incentivize individuals to take public transit instead of the paratransit service. In addition, my research findings suggest that providing free transit fares healthcare appointments will improve attendance rates, which will improve health outcomes and reduce overall healthcare costs. A policy recommendation is for healthcare providers to revisit the issue of how transit affordability impacts access to healthcare appointments. Next generation automated fare collection systems open the possibility for social service providers to easily transfer transit fares to clients' smart card.

* * *

(4) Fare payment decision making can be described by a two-tiered model, "scarcity mindset" does not appear to be universal, and many who choose to pay on a per-ride basis would have received a better value had they purchased a pass product.

I suggest a two-tiered decision making framework whereby an initial decision of whether or not to purchase a weekly or monthly pass has a down-stream effect on the need for affordability deliberation on a trip-by-trip basis. First, individuals must deliberate on whether to purchase a weekly pass or monthly pass. If a pass is purchased, subsequent decisions do not need to be made on a per-trip affordability basis. Alternatively, if an individual chooses to travel on a pay-per-trip basis, the decision making paradigm is very different. Trips are either forgone because of cost considerations or are made more complicated by efforts to optimize activities, maximize trips using free transfers, or even decide to ask the driver for a free or reduced-cost trip. A common theme throughout the interviews was that these conditions induce stress.

The *Scarcity Mindset* theory put forth by behavioral economists Sendhil Mullainathan and Eldar Shafir suggests that individuals with limited financial means are less successful in various aspects of life because living in poverty impedes cognitive capacity, not because they are of flawed character or inherently less capable. Being poor requires more cognitive capacity or bandwidth. This approach counters the dominant narrative that people are poor because they are personally incapable or unable to escape a culture of pathology. In doing so, it acknowledges structural problems such as the unequal distribution of wealth and historical institutional racism, but suggests that the burden of being poor itself affects the ability to function at the level of one's potential and make good decisions. The theory also proposes a potentially positive effect of scarcity, which is focus: being confronted with finite resources can lead to a focus that would not necessarily exist otherwise. These propositions are not necessarily well resolved. Through the interviews, I did not find evidence that the negative effects of the scarcity mindset are universal among low-income individuals.

Matching the data from participant smartcard records with data from their interviews, I was able to associate their revealed pass purchasing behavior with their reported decision making process. Though the number of participants interviewed was small, I found that, for the most part, each could be clearly categorized into one of these two archetypes: the *attentive planner* and the *inattentive planner*. Attentive planners described meticulous planning efforts to maximize mobility at minimal cost, and inattentive planners did not articulate an intentional effort to plan. Inattentive planners more often exhibited behaviors that ended up costing them more money than if they had purchased a pass in contrast to attentive planners. From this work, I draw the conclusion that low-income individuals exhibit the same variation of planning behaviors as those who are more financially well off. The time spent talking with participants reaffirms my conviction that the focus should be on remedying the structural causes of poverty, and not on reinforcing whether the poor are good decision-makers, even if the cause is poverty itself.

8.2 Limitations

A larger sample size of study participants would have narrowed the confidence interval around the treatment effect result. Validity bias is a common concern with randomized controlled evaluations. Though the postcard to 12,000 SNAP beneficiaries provided a well distributed outreach, participant selection bias is a concern. The sample represents those more comfortable with mobile phone texting, less skeptical of the establishment, and less concerned about privacy. The low participation rates for non English or Spanish speakers also limits the generalizability of the findings. The short study period of two months is another potential limitation. There may be temporal differences in individual travel behavior, seasonal differences in aggregate behavior, and an undetected *novelty effect* where the treatment effect may taper off over a longer time frame. The mere fact of participating in the study may influence travel behavior, possibly having a greater influence on the treatment group because those participants know they have received something special. Participants might believe that if they use the discount card more often than they would have outside of an experimental setting, policy makers will implement such a program system wide. This is a form of the *Hawthorn Effect* where individuals modify an aspect of their behavior in response to their awareness of being observed.

Another limitation is the use of proxies, such as number of trips taken and destinations, when the desired outcome variable is quality of life. Measurements of health and happiness would be preferred, but are challenging to measure and require a much longer time frame in order to do so. However, the conclusion that additional trips are taken when users are provided a subsidy is compelling evidence that transit affordability is an issue. Policy makers might incorporate normative judgments, suggesting that a discounted fare program might encourage "unnecessary" discretionary trips. Enabling more visits to friends and family, for example, might make for less compelling public policy than, say, improved access to healthy foods or increased access to healthcare. Taking a *right to the city* approach to equity and justice, on the other hand, provides a broader normative framework to drive public policy.

8.3 Future directions

There are a variety of future directions that can be taken based on the research presented in this dissertation. First, the participant sample generated a new smartcard dataset of low-income riders. Besides the time-of-day analysis presented, additional comparisons can be made against the average riding population. A future research opportunity would be to create a larger dataset of low-income riders which would provide more robust analyses that could also be conducted longitudinally. One of the barriers is the need to obtain individual consent to permit analysis of each person's data, as was done for my study. Growing fear of government monitoring and invasion of privacy, often of particular concern to low-income individuals, will make this effort challenging regardless of what safeguards are put in place.

It would also be worthwhile to explore whether a treatment effect continues even when the treatment is discontinued, a phenomenon identified by several researchers (Dupas, 2010). The theory would be that a short-term transit subsidy allows participants to experience increased mobility, enabling them to better appreciate and value the role of transit. The theory suggests that they would then exhibit an increased use of transit when the subsidy no longer existed. This behavior modification approach is not well understood beyond the field of consumer product marketing. Alternatively, there might be a *novelty effect* whereby the treatment effect diminishes over time even with a continued subsidy. A future experiment with a longer time period coupled with continued monitoring following study would offer additional insights into these aforementioned questions.

One of the findings from the study is that stress and forgone mobility occurs when individuals are paying for transit on a per-trip basis. At the same time, there is evidence that 30% of individuals who are paying for trips individually do not get *best value*, in that they would have been better off purchasing a pass product. Recent technological improvements in transit fare collection systems have opened up possibilities for innovations regarding fare products such as *fare capping* where customers pay for each trip individually but when a certain payment threshold is reached within a designated time period, subsequent trips in that period are automatically free. Such a program would provide financial relief to low-income individuals who previously were "over-paying" and stress relief at not having to contemplate the purchase of a weekly or monthly pass. But it would not solve the problem identified in my research where individuals who are paying for rides individually are in a constant state of stress regarding having to consider the cost of each trip. This paradigm would persist even with the implementation of a low-income fare. An alternative would be to only subsidize weekly and monthly passes, and not the per-trip fares, in an effort to nudge individuals toward those products. The tipping point for what that weekly cost would need to be in order to make it desirable requires further study.

When first discussing my project concept with officials at the DTA, they suggested a potential study design test whether transit cost is a barrier to meeting the work requirements for individuals characterized as *able bodied and without dependents* (ABAWD). A component of the 1996 Welfare Reform law, Federal policy dictates that only 3 full months of SNAP benefits in a three-year period is permitted unless individuals work, volunteer or participate in job training for at least 20 hours a week. Once an individual has reached their SNAP time period limit, they must wait three years before becoming, once again, eligible for a three month allocation. It is poorly understood why many individuals do not achieve the necessary work requirements. It would be useful to better understand whether inability to pay the transit fare is a significant contributing factor. The determination of what constitutes a three-year period varies state to state. Massachusetts chooses to fix the three year period in time, such that the clock resets for everyone at the same time. This last occurred on January 1, 2018 and will occur again on January 1, 2021. It would be useful to take advantage of this natural experiment to study the impact that subsidized or free transit has on enabling ABAWD individuals' abilities meet the work requirements. The benefit of this study design is that the dependent variable, meeting work requirements, is easy to measure, and treatment and control groups can be compared over time to see if transit affordability is a meaningful factor. Given the latest focus on work requirements, this would be a valuable research avenue to pursue.

Another idea, developed by my colleague Nick Kelly, would bridge housing and transportation. Currently, the Boston Housing Authority is running a program to support voucher-holder families in moving to a wider array of neighborhoods. Several of those neighborhoods are near commuter rail stations. The idea would be to provide a subsidy such that the cost of a monthly commuter rail pass would be equivalent to that of the monthly pass for the core transit system in Boston. In other words, someone using their voucher to move to that location could treat the commuter rail, which costs significantly more, as if it functioned as part of the core transit system. This would align nicely with the recent report on commuter rail affordability issues for access to Boston from *gateway cities*, which are home to many who have been displaced by the high cost of housing in Boston (Haney et al., 2019).

Finally, it would be worthwhile to explore connections between transportation subsidies and other social service objectives. Some policy advocates highlight that households with savings can better manage financial shocks, thereby reducing financial stress, but find that low-income individuals have difficulties saving for emergencies because of low wages and volatile incomes (Ain, 2019). Instead of providing a low-income transit discount at the time the trip is taken, equivalent funds could be automatically deposited into a special savings account which would become available to the participant after a certain waiting period, such as six months. Funds could be provided on pre-paid debit cards or bank accounts. Research on college savings accounts for low-income families found that, regardless of how small the starting amount, participants were more likely to continue saving (Beer, Ajinkya, & Rist, 2017). The technical implementation will be possible with the next-generation automated fare collection systems. The potential research directions presented above illustrate how transportation planners could better engage with other poverty alleviation programs to make more holistic approaches to improving the lives of low-income individuals.

I conclude with a brief reflection on positionality. As a white male from a middle-class background studying at MIT, I came to this research with preconceived notions and biases, conscious and unconscious, about: low-income individuals, the best way to approach transportation inequity, my responsibility to contribute positively to social problems, and the privilege that accompanies me when engaging in my work. The research design was not directly informed by low-income transit users themselves nor was it conducted by someone with that background. In reflecting back on my research endeavor, I wonder how things would have turned out if I had life experiences similar to those who participated in the study. Would I have taken a completely different approach to this research? Would I have chosen fare affordability as the public transit issue worth studying? Would I have utilized the same methodology? Would I have framed it differently? Though I consulted with numerous leaders and advocates representing underserved and marginalized populations, I was ultimately the one who decided what to study, designed the research, and implemented the study. Academics debate whether white investigators are qualified to study those who are primarily people of color (Tillman, 2002). An alternative approach I could have taken is Participatory Action Research, where "communities of inquiry and action evolve and address questions and issues that are significant for those who participate as co-researchers" (Bradbury, 2015). In the end, I hope the contributions of this dissertation are viewed positively by those whom I intended to help.

A

Maps


Massachusetts Bay Transportation Authority
Rapid Transit/Key Bus Routes Map
RL
ALEWIFE
Davis
Porter
Harvard
Central
Kendall/MIT
Charles/MGH
Park St
Downtown Crossing
South Station
Broadway
Andrew
JFK/UMass
Savin Hill
Fields Corner
Shawmut
ASHMONT
North Quincy
Wollaston
Quincy Center
Quincy Adams
BRAINTREE
Cedar Grove
Butler
Milton
Central Ave
Valley Rd
Capen St
MATTAPAN
OL
OAK GROVE
Malden Center
Wellington
Assembly
Sullivan Sq
Community College
North Station
Haymarket
State St
Chinatown
Tufts Medical Center
Back Bay
Mass. Ave
Ruggles
Roxbury Crossing
Jackson Sq
Stony Brook
Green St
FOREST HILLS
BL
WONDERLAND
Revere Beach
Beachmont
Suffolk Downs
Orient Heights
Wood Island
Airport
Maverick
Aquarium
Gov't Center
BOWDOIN
GL
LECHMERE
Science Park/West End
Boylston
Arlington
Copley
Hynes Convention Ctr
Kenmore
Prudential
Symphony
Northeastern
Museum of Fine Arts
Longwood Medical Area
Brigham Circle
Fenwood Rd
Mission Park
Riverway
Back of the Hill
HEATH ST
Blandford St
BU East
BU Central
BU West
St. Paul St
Pleasant St
Babcock St
Packards Corner
Harvard Ave
Griggs St
Allston St
Warren St
Washington St
Sutherland Rd
Chiswick Rd
Chestnut Hill Ave
South St
BOSTON COLLEGE
Kent St
Hawes St
St. Mary's St
Coolidge Corner
Summit Ave
Brandon Hall
Fairbanks St
Washington Sq
Tappan St
Dean Rd
Englewood Ave
CLEVELAND CIRCLE
Fenway
Longwood
Brookline Village
Brookline Hills
Beaconsfield
Reservoir
Chestnut Hill
Newton Centre
Newton Highlands
Eliot
Waban
Woodland
RIVERSIDE
SL1
SL2
SL3
SL4
SL5
Courthouse
World Trade Ctr
Silver Line Way
Harbor St
Tide St
DESIGN CENTER
(multiple stops)
AIRPORT TERMINALS
Logan International Airport
Herald St
East Berkeley St
Union Park St
Newton St
Worcester Sq
Mass. Ave
Lenox St
Melnea Cass Blvd
DUDLEY SQ
CHELSEA
Bellingham Sq
Box District
Eastern Ave
Lynn
Woodlawn
Revere Center
Chelsea
West Medford
Waltham
Waverley
Belmont
Arlington Heights
Watertown Sq
Watertown Yard
Union Sq (Allston)
Newtonville
Boston Landing
Needham Heights
Needham Center
Needham Junction
Hersey
W. Roxbury
Highland
Bellevue
Roslindale Village
Hyde Park (Cleary Sq)
Readville (Wolcott Sq)
Fairmount
Blue Hill Ave
Morton St
Talbot Ave
Four Corners/Geneva
Uphams Corner
Newmarket
Kane Sq
Codman Sq
Grove Hall
Franklin Park Zoo
LOWELL LINE
HAVERHILL LINE
NEWBURYPORT/ROCKPORT LINE
FITCHBURG LINE
WORCESTER LINE
NEEDHAM LINE
FRANKLIN LINE
PROVIDENCE/STOUGHTON LINE
FAIRMOUNT LINE
MIDDLEBOROUGH/LAKEVILLE LINE
KINGSTON/PLYMOUTH LINE
GREENBUSH LINE
HULL FERRY
HINGHAM FERRY
CHARLESTOWN FERRY
Charlestown Navy Yard
Long Wharf (North)
Long Wharf (South)
Rowes Wharf
Logan Ferry Terminal
Rental Car Center
Legend
RED LINE
MATTAPAN LINE
ORANGE LINE
BLUE LINE
SILVER LINE and branches
GREEN LINE and branches
Terminates at Park St
Terminates at Gov't Center
Terminates at N. Station
Terminates at Lechmere
COMMUTER RAIL
KEY BUS ROUTE
Frequent service
FERRY
Accessible station
All MBTA and Massport bus and ferry services are accessible
Rapid Transit transfer station
Commuter Rail transfer station
Free Logan Airport shuttle bus
Amtrak service
Back Bay, North & South stations
*Boylston: Accessible for Silver Line only
Customer Communications & Travel Info
617-222-3200, 800-392-6100,
TTY 617-222-5146, www.mbta.com
MBTA Transit Police: 911
TTY 617-222-1200
Elevator/escalator/lift updates: 800-392-6100
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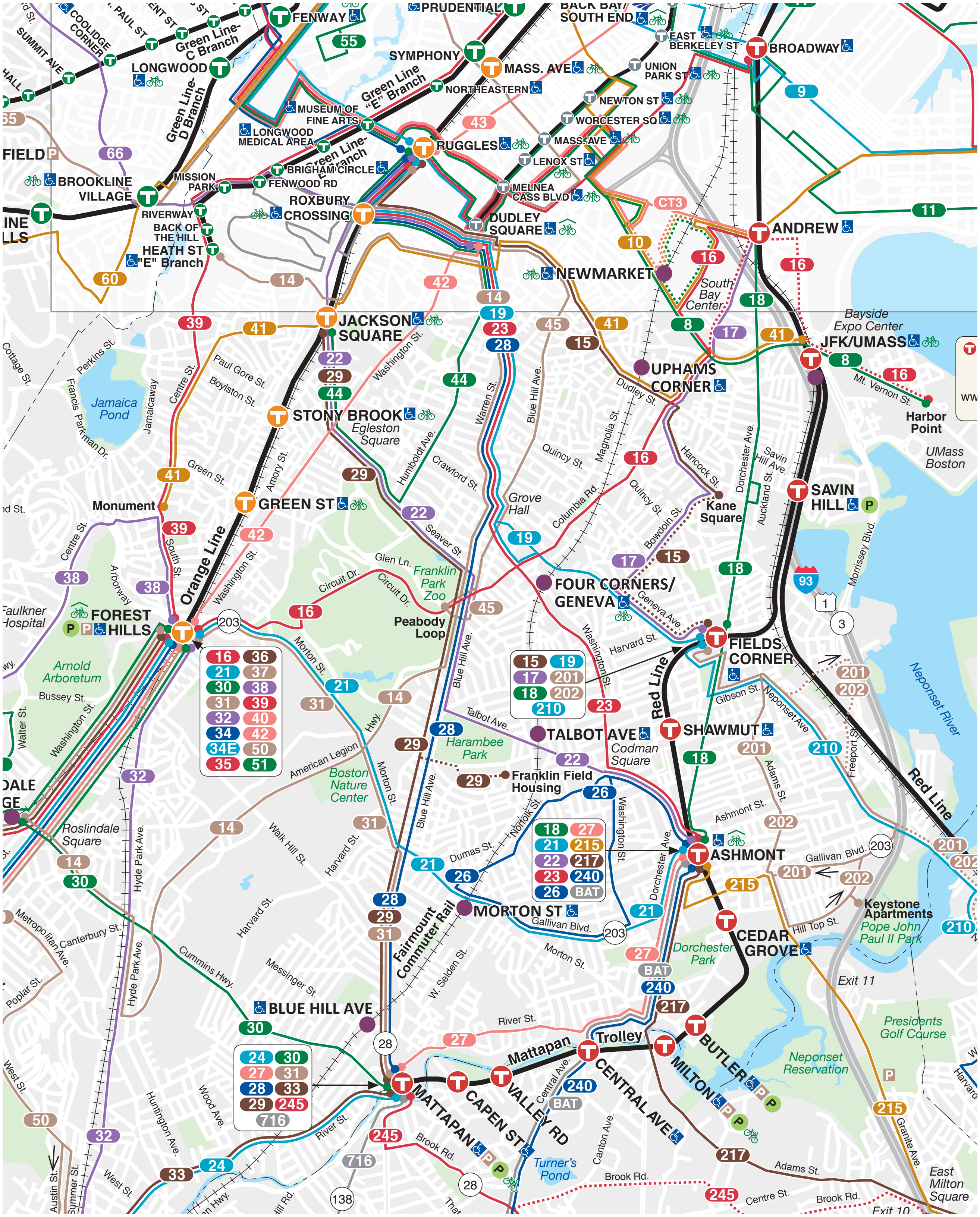
Not to scale


MALDEN
EVERETT
REVERE
CHELSEA
OAK GROVE
MALDEN CENTER
WELLINGTON
ASSEMBLY
SULLIVAN SQUARE
COMMUNITY COLLEGE
LECHMERE
SCIENCE PARK/ WEST END
NORTH STATION
HAYMARKET
BOWDOIN
GOVERNMENT CENTER
STATE ST
AQUARIUM
PARK ST
DOWNTOWN CROSSING
BOYLSTON*
ARLINGTON
CHINA-TOWN
TUFTS MEDICAL
SOUTH STATION
COURTHOUSE
WTC
SILVER LINE WAY
COPLEY
HYNES
KENMORE
LANSDOWNE
FENWAY
PRUDENTIAL
SYMPHONY
MASS. AVE
BACK BAY/ SOUTH END
HERALD ST
EAST BERKELEY ST
UNION PARK ST
BROADWAY
NORTHEASTERN
LONGWOOD
CENTRAL
KENDALL/MIT
CHARLES/MGH
CHELSEA
BELLINGHAM SQUARE
BOX DISTRICT
EASTERN AVENUE
WOOD ISLAND
AIRPORT
MAVERICK
Orange Line
Haverhill Commuter Rail
Green Line
Red Line
Blue Line
Rockport/Newburyport Commuter Rail
SL1
SL3
SL3 Branch
SL1 & SL3 Branch
SL2 Branch
Logan International Airport
Logan Airport
Logan International Airport Terminals
Charlestown Navy Yard
Charlestown Ferry
Long Wharf (North)
Long Wharf (South)
Rowes Wharf
Mystic River
Charles River
Union Square
Inman Square
Linden Square
Woodlawn
Everett Square
Cary Square
Quigley Hospital
Northgate Shopping Center
Cliftondale Square
Kennedy Drive
Lebanon Street Loop
Gateway Center
Meadow Glen Mall
Malden Medical Center
Medford Square
Lawrence Memorial Hospital
Elm Street
Doonan St.
Molineaux Circle
Middlesex Fells Reservation
Fells Reservoir
South Reservoir
Wright's Pond
Pine Banks Park
Market Basket
Assembly Row
SEE INSET
Express to/from Boston Haymarket Station
Express to Haymarket
434, 450 Express to Haymarket via R
Encore shuttle



FENWAY
PRUDENTIAL
BACK BAY/ SOUTH END
EAST BERKELEY ST
BROADWAY
COOLIDGE CORNER
SUMMIT AVE
Green Line- C Branch
LONGWOOD
SYMPHONY
MASS. AVE
UNION PARK ST
Green Line "E" Branch
NORTHEASTERN
NEWTON ST
Green Line- D Branch
MUSEUM OF FINE ARTS
WORCESTER SQ
LONGWOOD MEDICAL AREA
MASS. AVE
RUGGLES
LENOX ST
Green Line- E Branch
BRIGHAM CIRCLE
FENWOOD RD
MISSION PARK
BROOKLINE VILLAGE
MELNEA CASS BLVD
ROXBURY CROSSING
RIVERWAY
BACK OF THE HILL
HEATH ST
"E" Branch
DUDLEY SQUARE
NEWMARKET
ANDREW
South Bay Center
JACKSON SQUARE
Bayside Expo Center
JFK/UMASS
UPHAMS CORNER
Harbor Point
Mt. Vernon St.
UMass Boston
STONY BROOK
Egleston Square
Jamaica Pond
SAVIN HILL
Kane Square
Monument
GREEN ST
Grove Hall
Franklin Park Zoo
FOUR CORNERS/ GENEVA
Orange Line
Faulkner Hospital
FOREST HILLS
Peabody Loop
FIELDS CORNER
Neponset River
Arnold Arboretum
Red Line
SHAWMUT
TALBOT AVE
Codman Square
Harambee Park
Franklin Field Housing
Boston Nature Center
Roslindale Square
ASHMONT
MORTON ST
Fairmount Commuter Rail
Keystone Apartments
Pope John Paul II Park
CEDAR GROVE
Dorchester Park
BLUE HILL AVE
BUTLER
Trolley
Mattapan
CENTRAL AVE
VALLEY RD
CAPEN ST
MATTAPAN
MILTON
Neponset Reservation
Presidents Golf Course
Turner's Pond
East Milton Square
Exit 11
Exit 10


Red Line
ALEWIFE
Express to/from Burlington via Rt. 2 and Rt. 128
351
Acorn Pk. Dr.
Russell Field
Rindge Ave.
SEE INSET
DAVIS
Powder House Square
Fitchburg Commuter Rail
PORTER
Danehy Park
Fresh Pond
Fresh Pond Parkway
Concord Ave.
Huron Ave.
Grove St.
Blanchard Rd.
Bright Rd.
School St.
Belmont St.
Aberdeen Ave.
Mt. Auburn St.
Mt. Auburn Hospital
Mt. Auburn Cemetery
HARVARD
Union Square
Inman Square
CENTRAL
KENDALL/MIT
CHARLES/MGH
LECHMERE
SCIENCE PARK/ WEST END
Green Line
Red Line
SULLIVAN SQUARE
ASSEMBLY
Assembly Row
WELLINGTON
Mystic River
Mystic Valley Pkwy.
Glen Mall
Encore shuttle
Gateway Center
Broadway
Highland Ave.
Cedar St.
Medford St.
Mystic Ave.
Charles River Reservation
Soldiers Field Rd.
Western Ave.
N. Harvard St.
Watertown Mall
Nichols Ave.
Dexter Ave.
Arlington St.
Coolidge Ave.
Mass. Turnpike
BOSTON LANDING
Cambridge St.
Faneuil St.
N. Beacon St.
Union Square
Brooks St.
Market St.
Washington St.
Brighton Center
Foster St.
Charles River
ARLINGTON
COPLEY
HYNES
KENMORE
LANSDOWNE
PRUDENTIAL
FENWAY
BACK BAY/ SOUTH END
SYMPHONY
MASS. AVE
NORTHEASTERN
MUSEUM OF FINE ARTS
LONGWOOD MEDICAL AREA
BRIGHAM CIRCLE
FENWOOD RD
MISSION PARK
RIVERWAY
BACK OF THE HILL
HEATH ST
"E" Branch
RUGGLES
ROXBURY CROSSING
JACKSON SQUARE
DUDLEY SQUARE
NEWMARKET
NEWTON
WORCESTER
MASS. AVE
LENOX ST
MELNEA CASS BLVD
Green Line "E" Branch
Green Line B Branch
Green Line C Branch
Green Line D Branch
LONGWOOD
BROOKLINE VILLAGE
BROOKLINE HILLS
BEACONSFIELD
RESERVOIR
CLEVELAND CIRCLE "C" Branch
CHESTNUT HILL
Reservoir Park
Boylston St.
Reservoir Rd.
Chestnut Hill Ave
Lee St.
Warren St.
COOLIDGE CORNER
BRANDON HALL
FAIRBANKS ST
WASHINGTON SQUARE
TAPPAN ST
DEAN RD
ENGLEWOOD AVE
SOUTH ST
CHESTNUT HILL AVE
CHISWICK RD
SUTHERLAND RD
WASHINGTON ST
WARREN ST
ALLSTON ST
GRIGGS ST
HARVARD AVE
PACKARDS CORNER
BABCOCK ST
PLEASANT ST
ST. PAUL ST
BU WEST
BU CENTRAL
BU EAST
BLANDFORD ST
ST MARY'S ST
HAWES ST
KENT ST
ST. PAUL ST
SUMMIT AVE
Harvard St.

B

IRB and Legal Approvals

MIT Committee On the Use of Humans as Experimental Subjects

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
77 Massachusetts Avenue
Cambridge, Massachusetts 02139
Building E 25-143B
(617) 253-6787

To:	Jinhua Zhao 9-523
From:	Leigh Firn, Chair COUHES
Date:	02/28/2018
Committee Action:	**Expedited Approval**
COUHES Protocol #:	1801206182
Study Title:	Discounted Transit Fare Study
Expiration Date:	02/27/2019

The above-referenced protocol was approved following expedited review by the Committee on the Use of Humans as Experimental Subjects (COUHES).

If the research involves collaboration with another institution, then the research cannot commence until COUHES receives written notification of approval from the collaborating institution's IRB.

It is the Principal Investigator's responsibility to obtain review and continued approval before the expiration date. Please allow sufficient time for continued approval. You may not continue any research activity beyond the expiration date without COUHES approval. Failure to receive approval for continuation before the expiration date will result in the automatic suspension of the study and related research grants.

Information collected following suspension is unapproved research and cannot be reported or published as research data. If you do not wish continued approval, please submit Final Report Closure Form.

Unless informed consent is waived by the IRB, use only the most recent, IRB approved and stamped copies of the consent form(s).

Adverse Events: Any serious or unexpected adverse event must be reported to COUHES within 48 hours. All other adverse events should be reported in writing within 10 working days.

Amendments: Any changes to the protocol, including changes in experimental design, equipment, personnel or funding, must be approved by COUHES before they can be initiated, except when necessary to eliminate apparent immediate hazards to the subject.

Human subjects training is required for all study personnel and must be updated every 3 years.

You must maintain a research file for at least 3 years after completion of the study. This file should include all correspondence with COUHES, original signed consent forms, and study data.

MIT Committee On the Use of Humans as Experimental Subjects

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
77 Massachusetts Avenue
Cambridge, Massachusetts 02139
Building E 25-143B
(617) 253-6787

To:	Jinhua Zhao 9-523
From:	Leigh Firn, Chair COUHES
Date:	02/27/2019
Committee Action:	Renewal
COUHES Protocol #:	1801206182R001
Study Title:	Discounted Transit Fare Study
Expiration Date:	02/26/2020

The above-referenced protocol was given renewed approval following Expedited Review by the Committee on the Use of Humans as Experimental Subjects (COUHES).

If the research involves collaboration with another institution then the research cannot commence until COUHES receives written notification of approval from the collaborating institution's IRB.

It is the Principal Investigator's responsibility to obtain review and continued approval before the expiration date. Please allow sufficient time for continued approval. You may not continue any research activity beyond the expiration date without COUHES approval. Failure to receive approval for continuation before the expiration date will result in the automatic suspension of the study and related research grants.

Information collected following suspension is unapproved research and cannot be reported or published as research data. If you do not wish continued approval, please submit Final Study Closure Form.

Unless informed consent is waived by the IRB, use only the most recent, IRB approved and stamped copies of the consent form(s).

Adverse Events: Any serious adverse event or unanticipated problem must be reported to COUHES within 48 hours. All other adverse events should be reported in writing within 10 working days.

Amendments: Any changes to the protocol, including changes in experimental design, equipment, personnel, or funding, must be approved by COUHES before they can be initiated.

Human subjects training is required for all study personnel and must be updated every 3 years.

You must maintain a research file for at least 3 years after completion of the study. This file should include all correspondence with COUHES, original signed consent forms, and study data.

MEMORANDUM OF UNDERSTANDING
BETWEEN
THE DEPARTMENT OF TRANSITIONAL ASSISTANCE
AND
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

This Memorandum of Understanding ("MOU") is made by and between the Department of Transitional Assistance ("DTA"), located at 600 Washington Street, Boston, Massachusetts 02111, and the Massachusetts Institute of Technology ("MIT"), located at 77 Massachusetts Avenue, Cambridge, Massachusetts, 02139. DTA is the state agency responsible for administering various public assistance programs, including the Transitional Aid to Families with Dependent Children ("TAFDC") program and the Supplemental Nutrition Assistance Program ("SNAP"). Eligibility for these needs-based public assistance programs depends on specific financial and non-financial eligibility criteria. MIT is a private academic institution and is conducting research on the travel behavior of low income transit riders in the Boston region (the "Research Study").

WHEREAS, a Research Study protocol is approved by MIT's Institutional Review Board known as the MIT Committee on the Use of Humans as Experimental Subjects. Such approval is attached as Exhibit A and is made a part of this MOU;

WHEREAS, MIT requires the ability to conduct an efficient low-income study participant recruitment mailing in the Boston area such that MIT can conduct the Research Study in a rigorous and generalizable fashion;

WHEREAS, DTA's mission is to promote long term economic self-sufficiency and a more robust understanding of transportation barriers would be beneficial to DTA;

WHEREAS, this Research Study is solely designed and being implemented by MIT and is not in any way endorsed by DTA;

DTA and MIT hereby agree to the following terms:

1. MIT RESPONSIBILITIES

a. Provide DTA with the specific criteria from which to extract sample of names/addresses of potential study participants. The criteria include: (a) living within a half mile of an MBTA rapid transit stop or quarter mile of a "Key Bus Routes" stop; and (b) are not currently eligible for an MBTA Senior or Disability discounted CharlieCard.
b. Provide DTA with 10,000 pre-stamped, printed study recruitment postcards containing content as approved by the MBTA and DTA
c. Provide at least 10,000 blank laser-printer labels

d. Provide as many MIT volunteers as necessary to affix mailing labels to the study recruitment postcards Aside from affixing the mailing labels to the postcards, such volunteers shall not remove or retain DTA-provided labels or the information contained on them.
e. Provide an auto-reply text message through SMS text messaging interface, containing content as approved by DTA, when recipients text MIT expressing interest in the study. If the recipient responds in the negative, he/she will immediately be opted out.
f. Share any and all study results with DTA, including providing a copy of the final study report, and upon request by DTA, present study results to DTA staff.

2. DTA RESPONSIBILITIES

a. According to criteria provided by MIT, extract a random sample of 10,000 SNAP recipients to receive the study recruitment postcards.
b. Print mailing labels to be affixed to the pre-printed study recruitment postcards.
c. Provide a space for MIT volunteers to affix labels to the postcards.
d. Coordinate the mailing of the postcards through the DTA mailroom.

3. DATA EXCHANGE AND PRIVACY PROTECTIONS

Except as provided below, the Parties agree that DTA will not provide to MIT and MIT will not accept personal data from DTA in performance of this Research Study. MIT will handle any information MIT receives from SNAP recipients in accordance with a protocol approved by MIT's Institutional Review Board (IRB) for research involving human subjects, and such protocol shall comply with applicable laws and regulations regarding the confidentiality and safeguarding of personal data.

The Parties agree that all information contained in the mailing labels provided by DTA to MIT for Task 1.d. and all information received from postcard recipients who express initial interest in the study by texting "hello" in response to the study recruitment postcard but do not ultimately provide informed consent to participate as so defined in the study, including such respondent's name, address and cell-phone number, and any information from such respondents that is stored on the "chatbot" server (collectively, the "DTA data") contains personal data, and therefore, the following terms apply to the DTA data:

a MIT understands that the DTA data is considered "personal data" and the parties are holders as defined in M.G.L. c. 66A. The parties must comply with all federal and state laws and regulations applicable to the DTA data, including but not limited to 7 CFR 272.1(c), M.G.L. c. 66A, M.G.L. c. 93H, and M.G.L. c. 66, § 17A.
b. MIT shall limit access to the DTA data for the purpose as set forth herein and utilize appropriate safeguards which reasonably and appropriately protect the confidentiality and integrity of the DTA data and that prevent use or disclosure other than as permitted

under this MOU. MIT shall ensure that these individuals authorized to access the DTA data comply with all data protections and restrictions set forth herein.

c. MIT shall immediately notify DTA, both verbally and in writing, upon becoming aware of any use or disclosure of DTA data not permitted under this MOU, and immediately take all appropriate actions necessary to: 1) retrieve, to extent possible, the DTA data used or disclosed in the non-permitted manner, 2) make reasonable efforts to mitigate any harmful effect known to MIT as a result of its non-permitted use or disclosure of DTA data, 3) take any further action as may be required by any federal or state law applicable to the privacy and security of DTA data, and 4) cooperate with the DTA in taking any further appropriate and authorized legal action to retrieve the DTA data and mitigate harmful effects.

d. All information received from postcard recipients who express initial interest in the study by texting "hello" in response to the study recruitment postcard but do not ultimately provide informed consent to participate as so defined in the study, including such respondent's name, address and cell-phone number, and any information from such respondents that is stored on the "chatbot" server, will be destroyed by MIT as promptly as reasonably practicable, and in any event within [ninety (90)] days of receipt by MIT Destruction shall be in accordance with the standards set forth in NIST Special Publication 800-88, Guidelines for Media Sanitization. MIT will promptly certify in writing to DTA the destruction of such data.

e These obligations of confidentiality shall expire upon: (1) the departure of all MIT personnel from the DTA premises upon the completion of Task 1.d., provided that no MIT personnel retain any of the confidential information contained on the mailing labels; and (2) the information as described in Section 3.d is destroyed as required.

4. INTELLECTUAL PROPERTY AND PUBLICATION

a. MIT shall grant a DTA a non-exclusive, non-transferable and non-assignable license to use the study's research results in support of internal, governmental, non-commercial research or educational purposes.

b. MIT agrees to recognize the contribution of the DTA in all written or oral public disclosures concerning MIT's research using the data, as appropriate in accordance with scholarly standards.

c. The DTA and its affiliates shall not use the name "Massachusetts Institute of Technology" or any variation, adaptation, or abbreviation thereof, or the name of any of MIT's trustees, officers, faculty members, students, employees, or agents, or any trademark owned by MIT, in any promotional material or other public announcement or disclosure without the prior written consent of MIT's Technology Licensing Office, which consent MIT may withhold in its sole discretion. The foregoing notwithstanding the MBTA may make factual statements about the existence of the agreement without prior approval, including the description of research being conducted hereunder, solely to comply with (i) governmental disclosure obligations, (ii) the MBTA's reporting policies, or (iii) requirements of publications or journals.

5. **MOU MANAGERS AND NOTICES**

DTA and MIT shall each designate an individual to serve as their MOU Manager. The MOU Manager shall supervise the day-to-day operations under the MOU and shall serve as the contact for all matters related to this MOU In the event that a MOU Manager changes, the party requesting the change will provide prompt written notice to the other.

DTA designates Brittany Mangini as its MOU Manager. Notice requires a copy to:

Department of Transitional Assistance
Legal Division
600 Washington Street, 5th Floor
Boston, MA 02111

MIT designates Jinhua Zhao as its MOU Manager. For contractual matters related to this MOU, notice requires a copy to MIT's Office of Sponsored Programs, Michael Leskiw, mleskiw@mit.edu.

Any notices given under this MOU shall be a written communication directed by one party to the other party and will be deemed given upon delivery or deposited in the U.S. mail, first class, postage prepaid to the MOU Manager.

6. **AMENDMENTS**

This MOU may be amended at any time upon written agreement of both parties.

7. **TERM AND TERMINATION**

The term commences on the date that the MOU has been executed by each party and shall continue until completion of the study on June 30, 2019 unless terminated earlier in accord with the MOU. Either party may terminate this MOU for any reason upon thirty days prior written notice to the other party. DTA may terminate the agreement immediately if it determines that any term of the MOU has been violated.

IN WITNESS WHEREOF, the Department of Transitional Assistance and the Massachusetts Institute of Technology have caused this MOU to be executed as of the later of the two dates below:

DEPARTMENT OF TRANSITIONAL ASSISTANCE	MASSACHUSETTS INSTITUTE OF TECHNOLOGY
By Mary Sheehan	By: Michael E. Leskiw
Printed Name: Mary Sheehan	Printed Name: Michael E Leskiw
Title: Chief Financial Officer	Title: International Sr. Contract Adminstrator
Date: 12/10/18	Date: 12/5/2018

C

Mailings

MIT RESEARCH STUDY
Endorsed by the T-Riders Union and
the Mel King Institute for Community Building.

Massachusetts
Institute of
Technology

THIS CHARLIETICKET COMES WITH $2.75,
FULL FARE FOR ONE SUBWAY OR BUS RIDE

MIT Travel Behavior Study

Thanks for your interest!
Here is information about our 2-month study.

If you want to participate,
text YES to 617-229-6831 to get started.

How does it work?

RECEIVE
a special CharlieCard

You receive a **CharlieCard** with a special sticker on the back.

It works just like any other CharlieCard—you can add money or a pass.

It will come pre-loaded with value for **2 free rides**.

Always use this special card when take the subway or bus!

TEXT
when you ride transit

Our **ChatBot** texts you once a day asking about trips the day before.

Respond by texting back how many times you went somewhere on the subway or bus and the general purpose of those trips (such as grocery shopping, work, visiting family).

WIN
cash in daily lottery

Every day you respond you will be entered into **a lottery to win $5.**

There are **10 winners per day.** There are only 500 people in the study so your chances are pretty good!

Even if you didn't ride transit that day, you can still enter the lottery.

You need to provide consent to participate

We are required to ask for your consent to participate in our research study. Please read the attached consent form and let us know if you have questions. Here are the key points:

- Participation is **voluntary**. You can leave the study at any time without a penalty.
- All personal information will be kept **strictly private and confidential** and will not be shared with anyone at all for any reason whatsoever. At the end of the study, we will delete all of your personal information from our system.
- As a participant, **you agree to use the special CharlieCard** for all your transit trips, **agree to respond to daily Chatbot texts,** and **allow us to access your MBTA trip data.**
- We provide no payment for participation other than entry into the daily $5 lottery.
- The study purpose is to investigate how ordinary people use the MBTA to access jobs, schools, healthcare, shopping, and family and how fares affect travel behavior.
- The study is being run by Jeff Rosenblum at MIT. Call or text any time 617-453-8285 or email equitytransit@gmail.com .
- MIT does not anticipate any risks to you from participating in this study.
- You are not giving up any legal claims or rights by participating in this study.

To participate, text YES to 617-229-6831

Massachusetts Institute of Technology

CONSENT TO PARTICIPATE IN RESEARCH

MIT MBTA Travel Behavior Study

You are asked to participate in a research study conducted by Jeff Rosenblum, a graduate student, and Jinhua Zhao PhD, an assistant professor, from the Department of Urban Studies and Planning at the Massachusetts Institute of Technology (M.I.T.) You were selected as a possible participant in this study because you responded to our postcard and completed a short set of questions. You should read the information below, and ask questions about anything you do not understand, before deciding whether or not to participate.

PARTICIPATION AND WITHDRAWAL

Your participation in this study is completely voluntary and you are free to choose whether to be in it or not. If you choose to be in this study, you may subsequently withdraw from it at any time without penalty or consequences of any kind. The investigator may withdraw you from this research if circumstances arise which warrant doing so.

PURPOSE OF THE STUDY

The purpose of this MIT study is to see if MBTA fares affect the travel behavior of people currently with low-income.

PROCEDURES

If you volunteer to participate in this study, the following will be involved. You will receive a unique tagged CharlieCard, identified with a sticker. The card should be used for the duration of the two month study. Using this card will help researchers better understand how fare impacts travel behavior.

- This card will come preloaded with enough money for 5 rides on the subway.
- You can add money to the card just like you would with any other card.
- The card is only valid for two months. The card will be deactivated at the end of that period (any money left on your card will automatically be mailed back to you).

As part of the study, you will receive a text message to your mobile phone at some point each day asking about your MBTA trips the day before.

- The text will ask you to respond with how many trips and the purpose of each trip (such as, “went to the doctor”, “went to work”)
- Each day that you respond, you will be entered into a lottery to win $5. Five winners will be picked each day, and $5 will be mailed to each winner.
- You are eligible for the lottery on every day that you respond, even if you did not use public transit the previous day.

Participants in the study agree to allow MIT researchers to track the starting location, time, and date of their MBTA trips while participating in the study.

POTENTIAL BENEFITS

The purpose of the study is to help inform public policy makers regarding the potential to implement a low-income fare program at the MBTA.

PAYMENT FOR PARTICIPATION

There will not be any payment for participation, except that participants will be entered into a daily $5 lottery. Participants will also receive a card that comes with 5 included MBTA trips. Participants who are in the top 50% of consistent responders will be entered to win an iPad at the conclusion of the study. After the completion of the study, participants will be reimbursed 5 cents for every text message sent or received in connection with the study.

CONFIDENTIALITY

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission or as required by law. In addition, your information may be reviewed by authorized MIT representatives to ensure compliance with MIT policies and procedures.

Only the members of the team identified above, Jeff Rosenblum and Jinhua Zhao, will have access to the data.

At the end of the study, any personally identifiable information, including your name, phone number, and address, will be deleted.

IDENTIFICATION OF INVESTIGATORS

If you have any questions or concerns about the research, please contact Jeff Rosenblum at equitytransit@gmail.com or (617) 453-8285.

EMERGENCY CARE AND COMPENSATION FOR INJURY

If you feel you have suffered an injury, which may include emotional trauma, as a result of participating in this study, please contact the person in charge of the study as soon as possible.

In the event you suffer such an injury, M.I.T. may provide itself, or arrange for the provision of, emergency transport or medical treatment, including emergency treatment and follow-up care, as needed, or reimbursement for such medical services. M.I.T. does not provide any other form of compensation for injury. In any case, neither the offer to provide medical assistance, nor the actual provision of medical services shall be considered an admission of fault or acceptance of liability. Questions regarding this policy may be directed to MIT's Insurance Office, (617) 253-2823. Your insurance carrier may be billed for the cost of emergency transport or medical treatment, if such services are determined not to be directly related to your participation in this study.

RIGHTS OF RESEARCH SUBJECTS

You are not waiving any legal claims, rights or remedies because of your participation in this research study. If you feel you have been treated unfairly, or you have questions regarding your rights as a research subject, you may contact the Chairman of the Committee on the Use of Humans as Experimental Subjects, M.I.T., Room E25-143B, 77 Massachusetts Ave, Cambridge, MA 02139, phone 1-617-253 6787.

SIGNATURE OF RESEARCH SUBJECT OR LEGAL REPRESENTATIVE

This study will be conducted primarily through SMS text message, so consent will be obtained through text messages.

If you have read and understand all of the information above, please text CONSENT to (CHATBOT NUMBER). If you have any questions, please contact the researchers at (617) 453-8285.

Put this magnet on your refrigerator for convenience.

YOU MUST USE THIS CARD FOR
ALL YOUR MBTA TRIPS
DURING THE COURSE OF THE STUDY
(February – March)

MIT RESEARCH STUDY
Endorsed by the T-Riders Union and
the Mel King Institute for Community Building.
Massachusetts Institute of Technology

MIT Travel Behavior Study

Dear Participant: Thanks for agreeing to participate in our study. The study starts today and ends March 31, 2019. You can contact me at any time by phone or text at 617-453-8285 or email equitytransit@gmail.com.

Sincerely, Jeff Rosenblum, MIT PhD Student Jeffrey L. Rosenblum

Instructions

RECEIVE a special CharlieCard	**You must use this special CharlieCard for all your MBTA trips!** Contact us immediately if you lose your CharlieCard, change your mobile number, or change your address. This card **works just like any other CharlieCard**—you can add value at any MBTA fare vending machine, retailer displaying the "Charlie" logo, or on the bus. You can also add a weekly or monthly pass. It comes pre-loaded with value for **2 free bus or subway rides** (2 x $2.25) and is ready for immediate use.
TEXT when you ride transit	The **MIT ChatBot** will text you once a day (at about 9 am) asking about the purpose of your transit trips the day before. **Respond by texting back only where you went by bus or subway** the day before. (If you drove, took a taxi, got a ride, or bicycled, you can include that information in parentheses, but that is optional). Here are some example responses: • to work and then back home • visit my cousin then pharmacy then back home • drop off daughter at daycare then to work then home • school, grocery store, doctor's appt, (took a Lyft home) • dropped kids at school, job interview, picked kids up from school, went to Target If you didn't take any trips by bus or subway the day before, respond "none."
WIN cash in daily lottery	**Every day** you respond you will be entered into **a lottery to win $5.** There are **10 winners per day.** There are only 500 people in the study so your chances are pretty good! Winnings are mailed immediately as cash. **Even if you didn't take the MBTA that day**, you can still enter the lottery.

Put this magnet on your refrigerator for convenience.

This special CharlieCard gives you a
50% discount on every MBTA trip.
Or you can buy a $30 monthly Link pass.
(This card expires March 31, 2019)

MIT Travel Behavior Study

MIT RESEARCH STUDY
Endorsed by the T-Riders Union and
the Mel King Institute for Community Building.
Massachusetts
Institute of
Technology

Dear Participant: Thanks for agreeing to participate in our study. The study starts today and ends March 31, 2019. You can contact me at any time by phone or text at 617-453-8285 or email equitytransit@gmail.com.

Sincerely, Jeff Rosenblum, MIT PhD Student Jeffrey L. Rosenblum

Instructions for your 50% discount CharlieCard

<table>
<tr><td>RECEIVE
a special CharlieCard</td><td>You must use this special discount CharlieCard for all your MBTA trips!

Contact us immediately if you lose your card, change your mobile number, or change your address. When you report a lost card, it is immediately deactivated and a replacement mailed to you.
The card starts with $0.
You can add value at any MBTA fare vending machine, retailer displaying the “Charlie” logo, or on the bus. Every time you use the card, it only deducts half the fare ($1.10 subway; $0.85 bus; also ½ price on express buses).
You can also choose to add a monthly Link Pass for $30 valid on the subway and local bus. (Sorry, no weekly pass available).
The card expires March 31, 2019 and will stop working immediately.
Do not purchase an April pass.
Remaining cash value on the card will be mailed to you immediately.</td></tr>
<tr><td>TEXT
when you ride transit</td><td>The MIT ChatBot will text you once a day (at about 9 am) asking about the purpose of your transit trips the day before.

Respond by texting back only where you went by bus or subway the day before. (If you drove, took a taxi, got a ride, or bicycled, you can include that information in parentheses, but that is optional). Here are some example responses:
<code>to work and then back home</code>
<code>visit my cousin then pharmacy then back home</code>
<code>drop off daughter at daycare then to work then home</code>
<code>school, grocery store, doctor’s appt, (took a Lyft home)</code>
<code>dropped kids at school, job interview, picked kids up from school, went to target</code>
If you didn’t take any trips by bus or subway the day before, respond “<code>none</code>.”</td></tr>
<tr><td>WIN
cash in daily lottery</td><td>Every day you respond you will be entered into a lottery to win $5.

There are 10 winners per day. There are only 500 people in the study so your chances are pretty good! Winnings are mailed immediately as cash.

Even if you didn’t take the MBTA that day, you can still enter the lottery.</td></tr>
</table>

MIT RESEARCH STUDY
Endorsed by the T-Riders Union and the Mel King Institute for Community Building.
Massachusetts Institute of Technology

Contacte: Jeff 617-453-8285 o equitytransit@gmail.com

¿Como puede responder a ChatBot? Ejemplos:

fui a trabajar y volví a casa

visité mi primo, luego a la farmacia, luego regresé a mi casa

dejé a mi hija en el jardín infantil, fui al trabajo, regresé a casa

escuela, supermercado, médico, (volví en Lyft)

dejar niños en la escuela, entrevista de trabajo, recoger a los niños, fuimos a Target

Puedes ser tan detallado como quieras:

me llevaron a mi clase de computación, después tomé la silver line y el autobús 44 a mi casa

fui en autobús a dejar a mis hijos, fui a un feria de trabajo en autobús y metro, regrese a ruggles para tomar el autobús 43 para regresar a casa

Para viajes que hace frecuentemente, puede acortarlo:

Jardín infantil, trabajo, supermercado, casa

iglesia, amigo, casa

MIT RESEARCH STUDY
Endorsed by the T-Riders Union and the Mel King Institute for Community Building.
Massachusetts Institute of Technology

Contact: Jeff 617-453-8285 or equitytransit@gmail.com

Examples of how to respond to the ChatBot:

to work and then back home

visit my cousin then pharmacy then home

drop off daughter at daycare then to work then home

school, grocery store, doctor's appt, (took a Lyft home)

dropped kids at school, job interview, picked kids up from school, went to target

You can be as detailed as you want:

got a ride to computer class then then took the silver line and bus 44 back home

took a bus to drop kids off, went to a job fair by bus and subway, then back to ruggles to catch the 43 bus home because of the rain

For trips you take regularly, you can shorten:

daycare, work, grocery, home

church, friend, home

D

Semi-structured interview protocol

Semi-structured interview protocol

Introduction

My name is Jeff Rosenblum and I am currently a graduate student at MIT in the Urban Planning department. The overall purpose of my research is to better understand how people in the Boston area use the MBTA and the purpose of their trips. This is completely independent academic research and not affiliated with the MBTA. This interview is follow-up to the research study you participated in last spring. You are one of about 40 study participants who have been selected to be interviewed.

I really appreciate the time you are giving to me for this interview. It should take about an hour, but no more than an hour and a half. I will be asking you some personal questions about the types of places you go, how you get there, and your transportation experiences in general. There are no right or wrong answers, or desirable or undesirable answers.

If it's ok with you, I'm going to record this conversation to help me review what you had said when I get home, but no one will ever listen to it except me and it will be deleted after I finish my report. Neither the recording nor your responses will ever be connected to you in any way. For example, in my report you will be only be identified by a pseudonym, like "person #1".

This interview is voluntary and you can ask to stop the interview at any time with no penalty. After the interview, I will give you an envelope with $20 as a "thank you" honorarium for agreeing to share your time with me.

In order for me to conduct research like this, I need to obtain your consent. I emailed you a copy of the consent form to look over and I also have a copy here for you to have. It is exactly the same as the one that you agreed to for the study itself but adds this interview. The main purpose of the form is to ensure that you are aware of your rights as a research participant and agree to participate. Do you have any questions about the consent form?

PART A: Travel	Research purpose
1. Let's start by having you talk me through your day yesterday. I'm interested in the places you needed to get to, how you got there, and what the trip was like? Was this a typical day for you?	
2. {if didn't use the T yesterday}Now think of the last time you used the T. Can you talk me through what happened that day?	
3. Besides going to {destination(s)} you just described, are there other types of places you go using the T? Can you describe a trip to one of those destination? [if needed] In your ChatBot travel diary, you mentioned taking T trips to {locations}, can you describe some of those trips?	Destinations
4. As we both know, transportation in Boston can be at times frustrating. Can you describe a time when taking the T was stressful? What aspects of the trip made it stressful? {alternate} Can you describe a trip that you don't look forward to taking on the MBTA?	Mindset, stress
5. Can you describe a trip that you chose not to take the T and explain why not?	Foregone trips; barriers to transit
6. Can you describe a time when you took the T only in one direction? What could be different to have made it so that you would have taken the T for that trip?	Other barriers to transit
7. [if it didn't come up already] Do you own a car or have access to using a car?	Vehicle access
** several people included mention of using TNC or bicycle in their ChatBot diary, so inquire about that if this is the case.*	
8. [If mentioned TNC in ChatBot diary] In some of your ChatBot travel diary entries, you mentioned sometimes taking the T in one direction and an Uber or Lyft in the other direction. Can you describe a situation where you would do that?	TNC
9. [If mentioned Bike in ChatBot diary] In some of your ChatBot travel diary entries, you mentioned sometimes using a bicycle to get around. Can you describe a destination that you sometimes take a bike and sometime take the T?	Bike
PART B: Payment/affordability	
10. Now I'm going to ask some questions about how you pay for the T. Do you usually buy a pass or pay-as-you-go? [tweak based on response] Why do you choose to pay that way? [if it varies:] How do you decide whether to get a pass or not? [if weekly] Do you ever consider a monthly pass? [if needed, can reference their response in the pre-study survey]	Media choice, affordability
11. Do you ever pay cash on a bus? [if so] Do you just put it in as cash or do you first add it to your CharlieCard? [if did a lot of pay-as-you-go during the study] During the study you {describe top-up behavior and ask question about that}?	Top-up
12. [if pay-as-you-go:] Can you describe a time that you struggled to decide whether to take the T somewhere because of the cost?	Affordability; foregone trip

13. [* only if in treatment group] Looking at the information on the CharlieCard that you used during the study, I see that you [used pay-as-you-go:] did you consider getting a monthly $29 pass that was offered? [used monthly pass] Why did you decide to get a monthly pass?	Monthly pass decision
14. When you need to add money to your CharlieCard, how do you do that? [if at fare machines or retail:] Do you use cash to add money or a pass to your CharlieCard or do you use a debit or credit card? [if cash] Why do you prefer to use cash? During the study, you {information on exactly where they paid, how much added to card}, can you talk about that [question customized based on situation]?	Payment method
15. Have you ever seen someone be a little short on cash and only pay part of the fare on the bus? What did the driver do in that situation? Have you ever been a little short or had to borrow money for the fare?	Short payments
PART C: Health	
16. Now I want to shift things a bit to focus specifically on trips you take for healthcare purposes. To start, I want to get a general sense of your health. In general, would you say your health is: poor, fair, good, very good, or excellent? Can you tell me a bit about why you reported that? [if different than survey] You reported on the survey before the study started that your health is {self-rated health}, do you think things have changed since then?	Health conditions
17. {if didn't mention a health trip earlier in Part A} Think of the last time you needed to go to the doctor or clinic, can you describe how you got there? [if not transit] Can you talk about a time you want to the doctor or clinic on the T?	Healthcare trips
18. Is that an appointment you have to go to regularly, or just occasionally?	Chronic vs. occasional
19. Can you think of a time when you were late to an appointment? What caused that? Have you ever been late because of the T?	Transit reliability
20. Have you ever had to cancel an appointment because of transportation issues?	Foregone trip
21. Looking at your ChatBot diary responses, you reported taking {frequency} of trips for health care purposes. Can you describe some of the different locations you need to get to for those trips?	Distance from home, transit accessibility
22. Have you ever gone to a doctor or clinic appointment another way besides taking the T? Can you describe that? Why did you choose not to take the T?	Reasons for taking alternatives to transit
23. Are you a MassHealth member? [if so:] Has a doctor ever filled out a "prescription for transportation" also called a PT1 request for you to get free transportation to/from your appointment? Or did you ever fill out a MassHealth transportation reimbursement form? Or ever get a	Free transportation
PART D: Study participation	
24. Ok, the next set of questions is about your participation in the study last spring. First, can give me a sense of why you decided to participate in the	

study last spring? Can you describe what it was like and how you felt to be part of the study?	
25. Can you remember a time during the study when you took a trip on the T but didn't use the special CharlieCard?	Validation: missing trips
** The following are only for participants in the treatment group*	
26. I know it was a little while ago, but think back to {participation months} when you were using the discount CharlieCard. When you first got the discount CharlieCard, can you describe what it was like when you first started using it?	Transit use frequency; induced trips
27. Can you think back to a specific trip that you took only because you had a discount card, a trip you probably wouldn't have taken if you didn't have it?	Transit use frequency; induced trips
28. When the discount card expired on June first, can you describe what happened when you went back to the way you used to pay for the T?	Transit use frequency; induced trips
29. Thinking back to the trip {in 27}, what would happen if you had to that trip tomorrow, would you be willing take the T?	Persistence of behavioral change
30. Did you ever find it useful to sometimes lend out your discount card to a friend or family member (it's totally fine if you did, I'm just curious if it was valuable to you to share it)?	Validation: extra trips by others
PART E: ChatBot	
31. Finally, a few questions about the ChatBot. What was it like engaging with the ChatBot?	Comfort, relationship
32. How was it getting the requests daily?	Diary frequency
33. Looking at your participation in the study, it appears you responded {frequency, gaps, and other info about response rate, ask question about that, trying to get at whether the $5 lottery was a good incentive}?	Validation: missing trips; why respond or not
34. What kind of phone plan you have (such as pay-as-you-go plan or a monthly plan)? Do you have data included or do you usually use wifi for the internet?	Data plan
35. What kind of apps do use on your phone? If I was to have used an app instead of texting, what do you think of that?	App vs. texting

Conclusion

Ok, that's all I have for transportation questions I wanted to ask. Before I go, I want to see if you have any questions or comments about anything related to the study or any final thoughts you want to share with me?

Again, I really want to thank you for your time, it's incredibly helpful to find out directly from individuals like yourself how issues relating to the MBTA impact your life. Here is an envelope with a $20 "thank you" honorarium. My email and number are there as well if you have any follow-up questions or thoughts you can get in touch.

E

MassHealth's "Prescription for Transportation" (PT1)

Through the interviews, some participants indicated they took advantage of the free transportation service through MassHealth. The program, called *Prescription for Transportation* and nicknamed PT1, allows those enrolled in MassHealth insurance to receive private contracted paratransit ride service at no cost. Although supposedly only available to those who cannot use public transit for a doctor visit, this apparently is not well enforced. While this could provide necessary transportation to appointments for those who cannot afford the MBTA fare, it certainly would not be a cost effective way to provide such service from a government expenditure perspective. According to the latest Human Service Transportation Office annual report available online, 2015, each trip costs on average $23.[31]

The program works as follows. A doctor is required to first fill out and submit a "prescription for transportation" form. This must be done at least three days ahead of time. Transportation then picks up the customer from their home and brings them to the appoint-

[31] https://www.mass.gov/doc/fy15-annual-report-pdf/download

ment. Another vehicle picks them up after their appointment and brings them home. The assumption is that those who request this service are somehow physically unable to use public transit, such as someone with a broken leg or obesity, or there is no “reasonable” public transit access to the facility. There is a line on the form that asks *Is there a medical reason why the member (or guardian if accompanying a minor) is unable to use public transportation? (Yes, No). If Yes, please cite specific medical reason.* The program website indicates that this service is only available if “you are not able to access public transportation and/or private means of transportation.” Obtaining this data to better understand the intersection of this service with public transit.[32]

In addition, MassHealth also permits individuals to obtain reimbursement for transit trips, but it is very unclear how to actually file for this reimbursement with no information about this on the MassHealth website or transportation brochures. I only learned of the program through a 2016 brochure by *Medical-Legal Partnership Boston*[33]. This is the only user-friendly information about this program. The regulation detailing the program states the following:

> 130 CMR 407.431: *Reimbursement to Members for Transportation Expenses. (A) Reimbursable Expenses. Members may obtain direct reimbursement from the MassHealth agency in accordance with 130 CMR 407.431 (B) for public transportation expenses that the member incurred when traveling to services covered by MassHealth. (1) In order to obtain reimbursement for public transportation expenses, a member must obtain documentation from an authorized provider... Transportation receipts are also required when available. (2) Transportation costs must total $5.00 or more.*[34]

From talking with the Transportation Policy and Program Development Manager at

32 https://www.mass.gov/service-details/covered-services

33 http://cdn2.hubspot.net/hubfs/235578/It_Takes_Two_Guides/Public_Transporation_Reimbursement_Process_7.22.16.pdf?t=1470365193060

34 https://www.mass.gov/files/documents/2017/07/bad/trn-33.pdf

MassHealth[35], I discovered that there are hardly any reimbursements have been submitted. This is not surprising given that the program is poorly advertised. The challenge is, in part, the requirement that receipts be produced meaning that a transit rider must purchase a fare at a subway vending machine in order to obtain a receipt– no receipts are provided on the bus when money is added to a CharlieCard. An additional issue is the problem with how to reimburse participants using a pass product. He agreed that the program is poorly executed. Independently, I learned from a staff member at Action for Boston Community Development indicated that she has been working with a client to figure out how to obtain reimbursement through the PT1 program for transit costs when using a pass, but has been unsuccessful thus far.[36]

The tradeoffs between getting a free PT1 ride and paying for public transit appear dependent on several factors. The first is scheduling and coordinating. One participant indicated, "For my doctor's appointments, I could get a PT1 but many times I just forget to [order] it and it's supposed to be like three days in advance. And I'm usually like moving too much to call and, you know, schedule the doctor's appointment at the last minute. So then I just have to pay for the bus myself." The second is wait time. Several participants who used the service indicated that one problem is that the service gets to the appointment considerably early, as much as two hours early. In addition, the wait for the return trip can also be lengthy because the service does not know in advance how long the individual will have to wait for their appointment and how long it will last. "I get so agitated sitting in the waiting room forever, I just have to get out of there. So usually I take the bus home because it just seems so unfair to have to wait so long," someone said during one of the interviews.

[35] Phone conversation October 3, 2019
[36] Conversation November 19, 2019

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