

A Fare Approach to Attracting Transit Ridership After COVID-19

by

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Abstract

The COVID-19 global pandemic substantially depressed ridership on transit agencies across North America. While much is still unknown about the anticipated return of transit ridership after the pandemic, the exacerbation of previous work-from-home trends due to continued remote work policies can negatively affect transit ridership recovery and the use of traditional pass fare products. For example, an increase in work-from-home flexibility after employees return to the office is likely to affect the ongoing establishment of “pass multiples”, or the “break-even” point, for monthly passes. This thesis examines two case studies of potential new or modified fare products and one randomized control trial and suggests a strategy for transit agencies to attract ridership as employers reopen their downtown offices. The research analyzes the Massachusetts Bay Transportation Authority (MBTA), the regional transit agency for Greater Boston and one of the largest in the nation. A focus on commuter rail users and the Perq program (the corporate pass program at the MBTA) narrows the analysis to traditional peak commuters (AM and PM frequent peak riders). The first case study dissects a new pass option that was introduced early in the COVID-19 pandemic known as the Flex Pass. While an honorable attempt at providing a flexible pass option during a time of uncertainty, alternative pass structures and heavier discounts will likely be necessary to attract more users to this, or an alternative, fare product. Based on an analysis using pre- and during COVID-19 commuter rail individual passenger usage, an alternative more heavily discounted 20/30 (20 trips within 30 days) fare product is recommended to replace the Flex Pass along with increased discounts on the Monthly Pass. Additionally, a randomized control trial conducted just before the pandemic shows how an email marketing campaign can be used to increase pass product adoption among regular system users. Coupled with the new 20/30 fare product and an increased discount on the Monthly Pass from the first case study, the email marketing campaign can help quickly roll out a new product to meet ever-shifting travel behaviors. Finally, a new employer-based fare product, named the Mobility Pass (a pay-per-use product for employers that functions as an unlimited pass for employees and requires all benefits-eligible employees be covered and is heavily subsidized by the employer), is analyzed to show the ridership growth potential if rolled out to all employers in the Perq program (as well as those who use third party employee benefit administrators). These three tactics can be used to increase ridership as transit agencies seek to recover from a global pandemic and historically low ridership.

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Chapter 1: Introduction

In 2020, a global pandemic caused drastic declines in transit ridership as society adjusted to the virus by minimizing travel. Throughout the stay-at-home orders and limited capacity at indoor facilities, transit agencies were anticipating an eventual “return to normal” of pre-pandemic ridership. The goal of many agencies was to remain afloat during the limited travel period until herd immunity is reached and travel can once again continue. However, pre-pandemic ridership trends were not going well for transit. Since the mid-2010s, transit ridership was in decline in many cities across the United States. One reason for this decline is often placed on Transportation Network Companies (TNCs), such as Uber and Lyft. Yet at the same time fares have been increasing at many transit agencies with minimal capital improvements and often mediocre service reliability. The goal for transit agencies should not be a “return to pre-pandemic ridership” but rather a “build back better” mentality, as President Biden campaigned on during the 2020 U.S. elections.

This thesis tries to analyze how transit agencies can leverage the pandemic to attract more riders to counteract previous trends, specifically through new or improved fare products. Research suggests that many employers will be allowing more work-from-home flexibility for their employees, which may reduce the proportion of five-day-a-week commuters. Additionally, new fare technologies allow agencies to offer new fare products and conditions than previously available. These are taken into consideration and suggests policies and fare products that should help increase ridership. This thesis focuses specifically at the Massachusetts Bay Transportation Authority (MBTA), the transit agency for the Greater Boston region. However, many of the fare products and methods researched can be adopted at other transit agencies as well.

1.1 Motivation

As briefly mentioned, one central motivation for this thesis is to increase transit ridership after its precipitous drop from the COVID-19 pandemic. At the end of 2019, a new virus developed and was first identified in Wuhan, China. The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) rapidly spread around the world, first being diagnosed in the United States in early 2020. In Massachusetts, new COVID-19 cases were climbing in February and March, eventually causing the Governor to declare a state of emergency and institute a stay-at-home order (JHU Coronavirus Resource Center, 2020). MBTA transit ridership declined by 80-95% in the span of two weeks following the Governor’s orders (MBTA, 2021). Since then up until March 2021, ridership has improved modestly, but is still significantly below 2019 ridership levels. A primary motivation of this thesis involves using fare products and media to increase ridership on transit for when travel restrictions are fully lifted and commuting to offices returns to some degree.

The global pandemic is not the only motivation for this thesis. In fact, interest in exploring fare products to increase ridership began before the pandemic, as transit ridership was already in decline. The rapid adoption of TNCs coupled with increased transit fares and decreased service provision all play into the smaller recent decline in transit ridership. This decline is a concern for transit agencies, especially as Boston and other municipalities on the rapid transit lines are increasing in population. While increasing service provision and providing reliable service are the primary tool to recapture ridership, the MBTA could also explore new fare products that meet the diverse travel behaviors of users. Pass products are an attractive method to increasing transit ridership as they offer a zero-

marginal cost for users, incentivizing them to travel more often. The balancing consideration among transit agencies is with losing the revenue from heavy users who would save money on a monthly pass. However, the reverse can also occur, where users take transit more when each additional trip is free, thus becoming heavy users in the process.

In the past decade, research on transportation demand management (TDM) has grown, specifically looking at it through a behavioral science lens. Studies have shown the power of the default, the importance of order in choices, and the impact our peers have on our decision-making. Within transportation, studies have looked at price salience on usage. Rosenfield (Rosenfield, 2018) analyzed a new transportation benefits policy at the Massachusetts Institute of Technology (MIT) that replaced annual parking passes with daily charging (capped at the annual rate) and made bus and subway trips free for all employees (previously a 50% discount on pass purchases), among other policy changes. These policy changes led to a 10% increase in transit trips among MIT employees. The change in the pricing structure of transportation benefits made the parking price to be more salient (visibly seeing the daily parking charge) while decreasing salience on bus and subway costs (zero marginal cost for all employees, not just those who purchased a pass). While many municipalities have passed TDM ordinances, it is often employers that push the envelope by adopting strong TDM policies. However, the adoption of strong TDM strategies by employers is often the exception rather than the norm. Still, as employers play a critical role in the mode choice of employees, part of this thesis is dedicated to that dynamic.

The COVID-19 pandemic may have drastically reduced transit ridership, but it also created a “pattern break” for traditional commuters. While transportation demand modelers often assume people consider all possible options and modes when traveling, behavioral psychology suggests that people are creatures of habit. Rather than considering whether to take the train or drive every day, considering the travel time, costs, and other factors, people often stick with a commuting habit. This makes it all the more difficult to nudge people into different modes through TDM initiatives. However, the global pandemic forced many commuters to break their travel patterns, creating an opportunity for transit agencies to attract riders back before they become comfortable driving or taking another mode to work. This thesis argues that it is in the best interest of transit agencies to increase ridership by offering discounted passes to attract riders to their system before they choose alternative travel modes.

The importance of offering discounted passes may be even more critical given the potential of reduced work weeks and increased flexibility as employers bring workers back to the office. While it is uncertain how many employers will offer flexible work-from-home options for their employees or how many will change to four-day work weeks, reduced work weeks has critical implications on pass multiples. A pass multiple is the number of trips required to “break even” with a pass compared to pay per use. For example, if each bus trip costs \$2 and a monthly pass costs \$60, then a person would have to make at least 30 trips to “get their money’s worth” with a monthly pass. If employers reduce the number of days employees have to show up to the office, then the number of trips they would normally make in a month is reduced, potentially making it less attractive to purchase a monthly pass. While there is still a lot of uncertainty around this topic, this thesis will address the implications of a reduced work week on transit ridership.

Finally, the MBTA is in the process of procuring a new fare technology system, known as AFC 2.0. The new technology is expected to provide fare integration across modes, allow for new fare media to be used (i.e. contactless credit cards), and will be account-based for each passenger, among other things. As will be discussed in Nudging Users to Pass Products to Induce Ridership, account-based

fare systems provide additional marketing capabilities that can be used to nudge users to pass options. In addition, AFC 2.0 also gives the agency the ability to switch to a fare capping model (offering the benefit of a period pass in real-time, without the need to determine future use in advance), similar to the one at Transport for London (TfL). If implemented, fare capping would have significant implications on the analyses presented here. Therefore, the potential impacts from AFC 2.0 will also be addressed in this thesis.

1.2 Objectives

This thesis looks explicitly at the Massachusetts Bay Transportation Authority (MBTA) that serves the Greater Boston region. Within the MBTA, this thesis focuses on the commuter rail and corporate program (known as the Perq Program) riders. Those two subgroups were identified as they have high proportions of “traditional” commuters who work five days a week and travel inbound during the AM peak period and outbound during the PM peak period. However, there is a lot more heterogeneity in these groups than the traditional assumptions suggest. Part of this thesis will explore the heterogeneity of commuter rail and Perq program riders.

The central research question this thesis tries to answer is “how can the MBTA use fare products to attract and capture ridership as travel restrictions are lifted and commuters return to work sites?” To answer this question, this thesis analyzes three case studies that aim to expand the zero marginal cost benefits of passes to a wider audience and increase ridership in turn. The first case study analyzes a new fare product released for commuter rail over the summer of 2020 – the Flex Pass. The Flex Pass was quickly rolled out during the pandemic to provide flexibility (as the name suggests) for riders who are uncertain if they will reach the pass multiple on a Monthly Pass, given the unpredictability of travel during the pandemic. The second case study analyzes a marketing campaign designed to shift pay-per-use users on commuter rail over to passes. While it only targeted commuter rail users, this is because the capability to extend the campaign to bus, subway, or Perq riders was not possible during the study period. However, under AFC 2.0, the MBTA should be able to introduce the email marketing campaign on bus, subway, and Perq riders.

The third case study focuses on the Perq program and expands on a pilot run in 2016 using MIT employees and the “Mobility Pass.” The Mobility Pass is a product through Perq for employers that offers universal and zero marginal cost bus and subway trips for employees but is paid by the employer on a fare-per-trip basis to the transit agency. For example, if an employer has 100 employees and a Monthly Pass cost \$50, the employer could pay \$5,000 for each employee to get a Monthly Pass or, under the Mobility Pass, they would pay only for each use. As it is unlikely that all employees take transit to get to work, this saves the company from purchasing monthly passes for employees who do not take transit, while still offering them a zero marginal cost option. The analysis builds on the 2016 pilot and examines the ridership growth and revenue implications for the MBTA.

These three case studies take different approaches to incentivizing higher ridership, either through a new pass product, by nudging users into passes, or by increasing zero marginal cost coverage through employers. These case studies offer possible methods for transit agencies to increase ridership using the power of the zero marginal cost. There are certainly other possible avenues for increasing ridership that may be even more effective, such as increasing frequency on routes or improving service reliability, but this thesis focuses only on fare products. Other user segments could also be explored in further work, such as expanding the Mobility Pass structure to low-income users or university students. This research, however, focuses on commuter rail and Perq riders only.

1.3 Methodology

The methodology differs for each case study and will be further explained in each following chapter. However, the analysis is primarily quantitative and uses passive data collection, email intervention, and surveys. For the two commuter rail case studies, the primary passive data source is the mTicket app. No other fare collection method on commuter rail collects data that can be used in disaggregate analyses, so mTicket data, which is an account-based Automated Fare Collection (AFC) system, is used and scaled up to estimate overall commuter rail ridership (more on scaling in mTicket Scaling). Since it is an account-based system, emails are included in most accounts. Nudging Users to Pass Products to Induce Ridership utilizes the emails to nudge users into passes in a randomized controlled trial (RCT). Perq data relied primarily on bus and subway data from the farebox and faregate AFC system. Two surveys were distributed to Perq organizations in order to get a better understanding of their transportation benefits offered. The first was conducted in May 2019 and had a 25% response rate. The second survey was distributed in December 2020 and, while receiving just over 50 responses, was designed to better understand employer intentions on their return to work and transportation benefits policies as the COVID-19 pandemic subsides.

A note on commuter rail fare collection. Commuter rail does not have passive data collection set up with its fare collection system with all but one sale channel. The most common sale channels are from fare vending machines (FVMs) or sales offices for paper tickets, through Perq for Monthly Passes on Charlie Cards (the plastic card used on the bus and subway system), onboard via conductors, or through mTicket. Paper tickets (typically purchased at FVMs or sales offices) are shown and clipped by conductors, who walk up and down the aisles during the train ride. Monthly passes through the Perq program are called “Flash Passes” for commuter rail. The Flash Pass is a Charlie Card that can be used on the bus and subway system with a tag indicating it can be used up to a certain zonal fare on commuter rail. Users show, or flash, the pass to conductors to validate it. Flash Pass users get a new card each month to prevent fare evasion. On-board fare collection involves purchasing a ticket from a conductor and receiving a paper One Way or Round Trip ticket, which is immediately validated by the conductor. Finally, the mTicket app allows users to purchase tickets from the app and activate them so they can be validated by conductors.

1.4 Thesis Organization

This thesis is organized into six chapters. Chapter 2: provides a literature review on transit ridership during the COVID-19 pandemic, shifts in work-from-home attitudes, fare structures and policies, behavioral psychology in transportation, and employer transportation benefits. Chapter 3: analyzes the Flex Pass, a new fare product that was first offered in the summer of 2020 as a flexible option for users who were uncertain of their travel behaviors during the pandemic. The product design is examined, and alternatives are considered that could be more effective at increasing ridership and market share. As a potential way of increasing pass sales on both a Flex Pass and Monthly Pass, Chapter 4: analyzes the effectiveness of a randomized control trial designed to increase pass adoption on mTicket. Chapter 5: discusses the implications of rolling out the Mobility Pass to all employers in Perq in regards to ridership and revenue. Each chapter includes a discussion on how the case study could be used to increase ridership as travel and capacity restrictions are lifted after the COVID-19 pandemic as well as potential implications under the AFC 2.0 system. Finally, Chapter 6: summarizes the three case studies and offers potential avenues for future work.

Chapter 2: Literature Review

The COVID-19 pandemic devastated the transportation industry throughout the travel restrictions. Airlines had to ground planes and at one point were reported to be flying empty planes just to preserve their slot-use at airports (Koenig, 2020). Vehicular traffic dropped significantly at the beginning of the pandemic while rebounding as the year progressed. Data from the Traffic Volume Trends December 2020 report (Federal Highway Administration, 2020) show vehicle miles traveled declined by roughly 40% in April but rebounded to roughly a 10% decline year-over-year from June onwards. Even shipping was heavily impacted by the global pandemic. As highlighted in the New York Times article (Goodman, Stevenson, Chokshi, & Corkery, 2021; Sy, Martinez, Rader, & White, 2020), global shipping logistics have been jumbled due to drastic changes in demand and worker absenteeism from the pandemic. The Massachusetts Bay Transportation Authority (MBTA) reported declines of 80-95%, depending by mode, at the onset of the stay-at-home orders (MBTA, 2021).

While transportation from all sectors were gravely impacted by the coronavirus pandemic, transit ridership was among the most impacted modes. Transit ridership was heavily affected by the initial fear that riding crowded transit services could be a factor in spreading the novel virus. This was particularly visible from the early and severe outbreak in New York City. Employer motivation shifted from locating in dense areas for the agglomeration benefits, encouraging transit and active modes (i.e. walking and cycling) to reduce congestion, air pollution, and parking costs to a motivation to provide free parking to help employees avoid exposure of COVID-19 on transit. This shift in employer transportation benefits and the reduced traffic congestion from stay-at-home orders likely contributed to the disproportionate loss of ridership on transit.

Section 2.1 from this chapter reviews literature on the impacts of COVID-19 on transportation, with an emphasis on transit. Section 2.2 will continue the literature review but focus on the expectations on work-from-home policies among employers and their impacts on commuting. The following two sections in this chapter review literature on topics that influence the three case studies. First, Section 2.3 reviews literature on behavioral psychology on cost salience, which is used in Chapter 3. The section also explores the concept of “nudging,” which is central to the email marketing campaign in Chapter 4. Finally, Section 2.4 focuses on literature that covers employer transportation benefits and transit agency corporate programs. Within it is a literature review of the 2016 MIT Mobility Pass pilot study that is the basis of the analysis in Chapter 5.

2.1 COVID-19 and Transit Ridership Declines

The COVID-19 pandemic had devastating effects on the transportation industry. As aforementioned, travel across all modes had major declines in the early months of the pandemic. Some modes, such as driving, saw rapid recoveries to pre-pandemic levels while others, such as transit, continue to be well below pre-pandemic ridership levels. Not only were different sectors impacted by the stay-at-home orders, but different sociodemographic groups were impacted unequally to the travel restrictions. Many of the traditional office employment positions were able to shift to remote work while healthcare, grocery, and delivery employees (among others) had to continue working in person during the global pandemic. This often translated in a higher proportion of minorities and low-income individuals working in-person while wealthier and whiter individuals were able to work remote or shift to driving to work. This section examines those discrepancies, starting with modal differences in Subsection 2.1.1, then discussing sociodemographic differences in

travel behaviors in Subsection 2.1.2. The last subsection would lead into Section 2.2, which discusses work-from-home policies during the pandemic and the predictions for after the pandemic.

2.1.1 Ridership Trends Estimated from on Navigation Apps

As previously mentioned, transportation was heavily impacted by the COVID-19 pandemic and regulatory stay-at-home orders by regional governments. Transit, however, has been impacted disproportionately compared to other local travel options. Many navigation apps have released data reports on demand by mode compared to a pre-pandemic baseline. Apple Maps (Apple Maps, n.d.), for example, continuously updates data on travel requests by mode throughout the pandemic to estimate travel trends from a baseline of January 13, 2020 (see *Figure 2-1*). The data is available for download in csv format and shows the requests made by region for driving, walking, and transit. As can be seen, walking and driving have already surpassed the baseline (note that the baseline does not account for seasonality) in the United States while transit trends are still below the baseline. In Boston specifically, walking and driving are at lower levels than nationally while transit requests match national trends. This could potentially be due to stricter reopening policies in Massachusetts compared to other States.

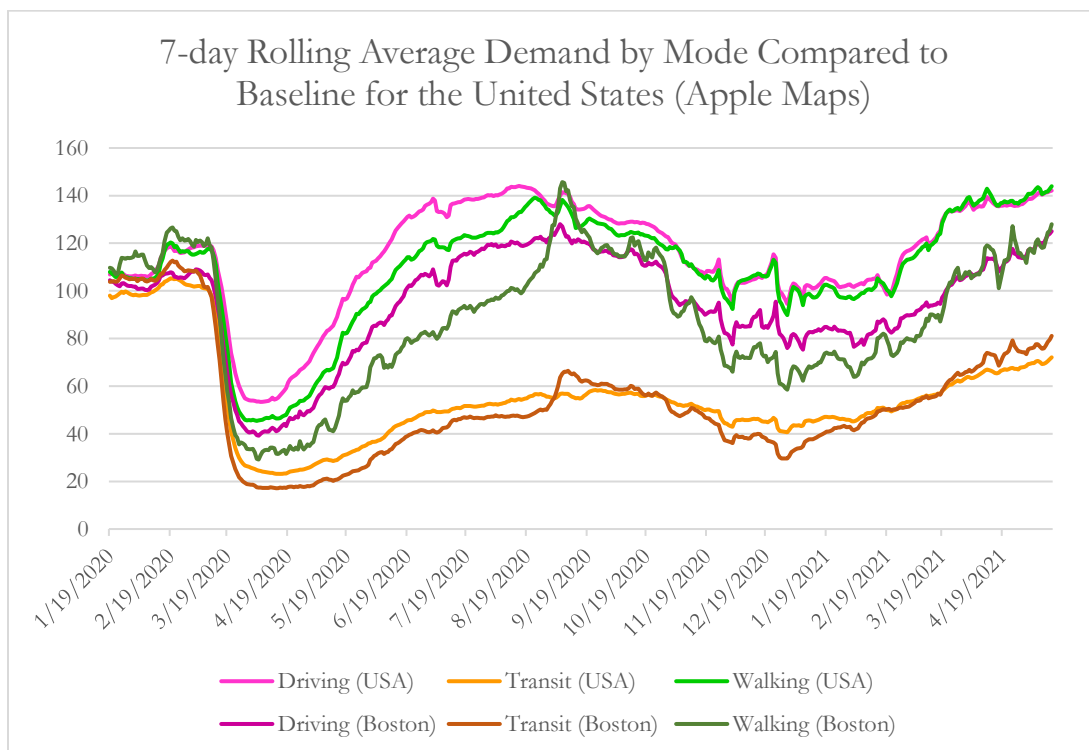


Figure 2-1: Driving, transit, and walking demand on Apple Maps in the United States and Boston from January 2020 to May 2021

Google has also provided travel information by region; however, it only provides information on the six most recent weeks (Google, n.d.). Instead, the Google data compiles the change in visits to categorical destinations compared to the baseline (the baseline is the median of a five-week period from January 3, 2020 to February 6, 2020 and compares against the day-of-week). One of the six categorical destinations is transit stations, which includes a wide range of potential locations, including subway stations. The other five destinations are retail and recreation, grocery and pharmacy, parks, workplaces, and residential. In the United States and Massachusetts, as of May

2021, visits are slightly below the baseline for retail and recreation (around 10% lower) and significantly below baseline for transit stations and workplaces (around 24-29% nationally and 37-44% in MA). On the contrary, visits to parks are significantly higher from the baseline (27% higher nationally and 39% higher in MA). Visits to grocery stores and pharmacies and residential areas are slightly higher than the baseline (under 10%). The Google data is more useful for understanding recent trends by trip purpose, compared to overall ridership trends.

Finally, transit-specific navigation apps (such as the Transit (Transit (App), n.d.), Moovit (Moovit, n.d.), and Citymapper apps (Citymapper, n.d.)) have also published reports on ridership declines based on their app usage. The Transit app even partnered with the American Public Transportation Association (APTA) using their data to create a dashboard of ridership trends across the United States and by transit agency (Transit and APTA, n.d.). Since each app only estimates based on those who use their product, the ridership estimates differ. For example, Citymapper estimates Boston travel to be around 21-39% of the baseline for October 2020, depending on the day. Moovit, however, estimates ridership to be 53-57% of the baseline and Transit estimates 29-49% of the baseline for the same month. Depending on mode, the MBTA estimates between 12% (commuter rail) and 47% (bus) of the baseline for October 2020.

Ridership estimates from these various navigation apps are useful for comparing how a region or mode is doing compared to another. However, they are not consistent across each other and are unlikely to provide accurate data on ridership on the system. Instead, the specific agencies have the closest to the ground truth of ridership numbers. Nonetheless, it can be useful to compare cities to one another on each app and see how one mode fares to another (i.e. transit compared to driving).

2.1.2 Transit Ridership by Socioeconomic Demographics

While transit ridership declined precipitously across the nation, the riders who left the system were not the same as those who remained. Many studies found those who were taking transit early in the pandemic were more likely to be low income, non-white, and female (Sy et al., 2020; Hu & Chen, 2021; and Transit, 2020). However, a study of New York City subway usage by zip code found that these factors were not significant when accounting for the proportion of “essential workers” in each zip code (Sy et al., 2020). This highlights the difference between transit riders who were still traveling early in the pandemic compared to those who left the system. First, the positions that were considered “essential” (i.e. grocery stores, transportation delivery, utilities, etc.) are more likely, in aggregate, to pay less. Those who were furloughed or able to switch to working remotely or drive to work tend to be higher paying jobs. The distinction between the work-from-home and “essential” work is important in the impacts they had on public transit ridership during the pandemic.

Due to the necessity of keeping grocery stores open and stocked and hospitals staffed, transit riders early in the pandemic were overwhelmingly non-white and female. The Transit app surveyed 25,000 users in March and April of 2020 who were still using their app to better understand how demographics changed behavior during the pandemic (Transit (App), 2020). The survey found a steep drop-off of white, male riders, and a higher retention of ridership from women and people of color. In fact, 70% of black riders during the pandemic were female. The survey also asked about trip purpose and found that 92% of respondents reported using transit to get to work. This proportion likely decreased in the summer and early Fall as leisure travel increased and stay-at-home restrictions eased.

The jobs that still required in-person employees were along the lines of healthcare, grocery, food processing, and delivery work. From Milder (2020), the industries that have the lowest work-from-home shares are the retail trade (14%) and food and accommodations (4%). Many of the jobs in these fields offer low wages compared to the typical office job that can shift remotely. When asked what profession they were in, the respondents to the Transit app survey were primarily in food preparation and healthcare support jobs. In addition, over 70% of respondents indicated that they earn less than \$50,000 per year. A study from Liu et al (2020) used ridership decline data from the Transit app to compare 113 cities on what factors correspond to a higher ridership decline. The study found lower ridership retention in cities with higher proportions of employees working in “non-physical occupations” (i.e. jobs that can be done remotely). On top of that, the researchers found a negative correlation between the proportion of the population that is Hispanic and the ratio of non-physical occupations, which suggests that Hispanics work primarily in jobs that were still in-person during the pandemic. Finally, the proportion of African Americans was one of the most important variables on predicting transit ridership retention (Liu et al., 2020).

Using station-level ridership data from the Chicago Transit Authority (CTA) and demographic and land use data from the American Community Survey (ACS), Hu and Chen (2021) found the COVID-19 pandemic and stay-at-home orders led to a 72.4% drop in ridership. Stations in areas with higher proportions of white, educated, and high-income individuals showed higher declines in ridership. Conversely, a higher proportion of black individuals resulted in a lower ridership decline as did a higher concentration of jobs in the trade, transportation, and utility sectors (Hu & Chen, 2021).

A significant factor in the ridership decline is from the remote work capabilities of certain industries. Sy et al. (2020) suggests that non-white and lower income neighborhoods traveled more on the NYC Subway due to the inability to work from home in their jobs. This matches their results of higher subway usage from healthcare and essential workers. Brough et al. (2020) found that ridership in King County, Washington was largely explained by the education level of each region. This was further illustrated when accounting for which industries that were capable of moving remotely. Using previous studies on the capabilities of different industries working remotely and pairing it with household access to a computer, smartphone, and the internet, Brough et al. found these work-from-home proxies as explaining a significant portion of the socioeconomic gap in travel behavior (Brough et al., 2020).

2.2 Work-from-home Under COVID-19 and Anticipated Employer Policies

Remote work increased significantly during the pandemic. However, not all industries were able to shift remotely and those who did tend to employ more educated workers, further explaining the economic disparities between transit riders and those who left the system. So how many employers and employees have shifted to working remotely? And how many will continue after the pandemic is over? According to a series of Gallup polls from April 2020 to September 2020, employees who indicated that they always work remotely decreased from just over half in April to around one-third in September. The proportion of employees who always work on-site increased from 31% in April to 42% in September, matching the phased reopening in states (Brenan, 2020). As vaccine distribution increased and government regulations loosened, on-site work has increased in 2021.

Those numbers roughly match the estimated proportion of jobs that can be performed entirely at home. Dingel and Neiman in a white paper estimated that 37% of jobs in the United States could be performed remotely (Dingel & Neiman, 2020). In addition, these jobs were found to pay more than their on-site counterparts. Dingel & Neiman estimate that 46% of all wages in the U.S. are from jobs that can be performed remotely. A significant portion of the workforce is able to (and did) work remotely, especially during the COVID-19 pandemic. The question, however, is if these jobs will continue to work remotely post-pandemic.

In a study early on in the pandemic, Bartik et al (2020) estimate around 40% of large and small firms expect to have 40% of their employees continue working remotely after the pandemic. This translates to at least 16% of employees working at least twice a week from home (Bartik et al., 2020). However, employer opinions on workforce productivity while being remote has changed a lot throughout the pandemic. In a survey to executives and office workers in November and December 2020, Pricewaterhouse Cooper found 83% of executives say working remotely has been successful for their company. This was slightly higher than the 73% who expressed a positive take on remote work in their June 2020 survey. The survey at the end of 2020 also found that 87% of executives intend on returning to the office in some capacity. The exact extent of that return to the office is unknown.

While the pandemic shifted a significant portion of the U.S. economy to working remotely, it is unclear how much of the work-from-home policies will remain after the pandemic. Milder (2020) describes this dilemma as the difference between trends and trend breezes. Trends are existing patterns that show a shift from one thing to another. A trend breeze, however, is an expectation of a trend without the certainty of it truly occurring. In this case, the shift to working from home is a trend breeze with incomplete information on whether the trend solidifies post-pandemic or dissipates back to previous work-from-home rates. However, even previous work-from-home estimates were inconsistent. The American Community Survey estimated around 3% of the workforce being remote before the pandemic. Milder compares that to two Gallup polls conducted in 2012 and 2016 that estimated 9.4% and 13.3%, respectively, of employees working at least 80% remotely. In addition, a study by Kotkin and Cox in 2014 estimated that employees working at downtown offices were more likely to work from home (about 13%) than the national average (Milder, 2020). It is unclear what proportion of the workforce, especially in cities, will remain working from home, and to what extent after the pandemic.

To get a better picture of the work-from-home policies employer intend on making after the pandemic, this research includes an employer survey that was distributed by the MBTA to its corporate program employers and through other channels (more information on this survey can be found in Section 5.7.1). The survey found (when removing those who were uncertain of their post-pandemic work-from-home policy) 72.1% of employees working full-time at the work site after the pandemic and 26.6% working partially remote. The last 1.3% of employees intend on working fully remote, according to their employers. While just over one percent of employees will be working remote, this corresponds to 12.8% of employers. However, most of those employers are small and do not employ many people.

2.3 Behavioral Psychology and Transportation

Transportation demand research has historically been examined from traditional economics lens. People are assumed to be fully rational beings that make decisions based on perfect information and pick the option that best fits their context. More recently, however, transportation demand is being

explored through psychology and behavioral economics, which examines the “irrational” but predictable decisions that people make. Behavioral economics tries to understand why humans and their actions might deviate from a “rational” decision or action.

In traditional economics, the cost of an item is not assumed to be different based on the medium it is purchased on. Behavioral economics, however, recognizes that price salience is an important component in human decision-making. Price salience is the recognition of the cost of an object. The more salient the price is, the more someone is aware of its relative cost. In a study comparing toll facilities with electronic toll collection (ETC) systems, Finkelstein finds that tolls are around 20-40% higher on the ETC system than they would be otherwise. Additionally, the elasticity from increases in the price of the toll decreases under an ETC system (Finkelstein, 2009). This highlights the impact of price salience. People who pay a toll at a toll booth physically experience the exchange of money from their wallet to the toll booth operator. Electronic tolls, however, immediately charge the user the toll either from a device inside their vehicle or by sending a bill to their home. The lack of constantly seeing the cost of an object makes the user more inelastic to increases in the cost.

Another way to reduce price salience is to provide a monthly or annual pass. This reduces the salience of the per-usage price as the object is purchased once over a longer period. Instead, usage is typically higher as the purchaser tries to make up the value of the pass. In complying with requirements when building the new headquarters for the Gates Foundation, the foundation reduced drive alone rates from 90% (from the previous location) to 34% (at the new headquarters) when they (among other things) removed the free parking and instead charged \$12 daily (Gutman, 2017). The daily fee made the cost of parking more salient, meaning employees were reminded daily of the cost of parking.

The traditional transportation demand modeling assumes people examine the options by the costs and benefits attributed to each and make a decision that best fits their self-interest. However, studies in behavioral psychology have shown that people tend to follow the habits they form around transportation. A study from Møller & Thøgersen (2008) found that the more entrenched a driver is in their habit of driving, the less they would intend to take public transit (Møller & Thøgersen, 2008). It can be difficult to break habits once they are formed, even with nudges. This has important implications in regards to the COVID-19 pandemic, which uprooted many commuting patterns. This “pattern break” offers a new opportunity to nudge people onto transit before they rebuild any earlier habits of driving.

Møller & Thøgersen in another study researched the intended behaviors of 1,000 auto commuters on taking public transit if they were offered a free transit pass. Their research found that offering a free transit pass leads to increased transit use by habitual drivers. However, it was also possible to reduce driving rates when participants were asked to perform a planning exercise that prioritized transit usage. Other studies have also confirmed the impact of trip planning in shifting users away from driving (Rosenfield, 2018; Whillans et al., 2020). However, Whillans (2020) notes that attempts at nudging users away from driving often yield minimal shifts (none of their experiments saw greater than 9% in behavioral change). Additionally, a few experiments did not show any statistical significance in changed behavior (Whillans et al., 2020).

Rosenfield (2018) and Whillans (2020) both use randomized controlled trials (RCTs) in their experiments. RCTs are considered the gold standard in the medical field since it tests cause and effect relationships better than other experiment designs. An RCT is where participants are separated into two (or more) groups, one being a treatment group and the other the control.

Placement into the groups is random so as to avoid biases. The control group is not given any intervention and used as a check on the efficacy of the treatment. Rosenfield implemented an RCT with employees at the Massachusetts Institute of Technology (MIT) by separating employees into four groups. One group received a monetary incentive to reduce driving trips to campus, another received an informational pamphlet discussing the environmental and health benefits of other modes, one group was given the monetary incentive and the informational pamphlet, and the final group was a control. The results found a slight decrease in parking and an increase in transit usage by all three treatment groups, with the combined treatment group experiencing the greatest decline in auto use and higher transit increase.

2.4 Employer Transportation Benefits

Local and regional governments have tried using regulatory tools to address transportation-related issues (i.e. congestion, air pollution, climate change, etc.) through what are known as Transportation Demand Management (TDM) programs. In general, TDM programs serve as a set of potential tools of carrots and sticks to nudge people towards or away from certain travel modes. In Cambridge, MA, the Parking and Transportation Demand Management (PTDM) ordinance applies to property owners who add more than four parking spaces. The owner must comply with at least three TDM measures and, if they add twenty or more spaces, would have to monitor and report their single occupancy vehicle (SOV) rates. Examples of potential TDM measures are subsidizing transit, charging drivers for parking, provide shuttle service to or from MBTA stations, incentivize carpooling, providing bicycle amenities, and more.

While TDM programs often target employers at given locations, there is less emphasis on the employer transportation benefits bundles. A study of commuters in New York and New Jersey found that commuters' mode choice was most influenced by the transportation benefits offered by employers (Bueno et al, 2017). Benefits that subsidized driving (i.e. free parking, toll reimbursement, etc.) resulted in a decreased likelihood of commuting on public transit over a car by 82%. Conversely, public transit subsidies were the primary variable in explaining transit as the mode of choice. Employer transportation benefit bundles play a major role in influencing employee mode choice.

Employers have been able to deduct transportation benefits from employee payroll before applying taxes since the 1970s. In 2014, TransitCenter estimated that those pre-tax payroll deductions, specifically regarding parking benefits, resulted in \$7.3 billion less tax revenue to the federal government (TransitCenter and Frontier Group, 2014). That parking benefit is estimated to add an additional 820,000 SOV commuters each year. The parking tax deduction is only applicable to around a third of commuter as parking in suburban and rural areas do not benefit from this tax deduction by the Internal Revenue Service (IRS). In a separate TransitCenter report from 2017, only 7% of workers are offered a subsidized transit benefit, and only 2% actually use that benefit (TransitCenter and Frontier Group, 2017).

Parking policy is typically viewed as the primary factor that dictates employee mode choice. A study of 4,630 commuters around the Washington D.C. region found free parking to be the single most influential variable in predicting drive alone mode share (Hamre & Buehler, 2014). If employers only offer free parking as a transportation benefit, the model suggests that there is a 96.6% probability of employees driving to work. If free parking were paired with transit benefits, that probability would decline to just 82.9%, indicating that transit benefits are not enough to nudge commuters away from parking.

Free parking influencing drive alone commuting has been discussed since the 1980s with early studies from Donald Shoup estimating that around 90 percent of drive alone commuters receive free parking at work (Shoup, Parking Cash Out, 2005). To counteract this correlation and decouple the impact of free parking with its influence on parking, Shoup suggests a parking cash-out option. A parking cash-out is a policy by employers where parking remains free but a cash benefit equal to the cost of subsidizing parking is offered to employees who get to work by another method besides driving. Thus, free parking can still be offered as a transportation benefit, but employees then have to choose between the parking benefit and a cash benefit equal to the cost of parking. For instance, if fully subsidizing parking costs \$200 per space per month by an employer, the employer would continue to subsidize parking while also offering \$200/month to employees who commute via transit, walking, cycling, or any other mode besides driving. The calculus becomes whether employees wish to drive to work or receive a cash bonus in its place.

From examining seven case studies in LA, DC, and Ottawa, Shoup found that providing free parking increased the number of cars driven to work by 36 percentage points (includes carpool and drive alone shares). One-quarter of employees switched to driving alone when free parking was offered. California passed a parking cash-out requirement for employers with at least 50 employees who lease their parking spaces. Shoup examined eight of the employers that offered parking cash-outs and found an average reduction of 13% of employees shifting away from driving alone with a range of 3 to 22 percentage points. The smallest shift was from a firm that already offered a partial parking cash-out before increasing the benefit to the full cost of the parking subsidy. The highest reduction in drive alone shares came from an employer that offered a parking subsidy of \$100/month or a cash benefit of \$150/month, exceeding the California requirement (Shoup, Parking Cash Out, 2005). Thus, the benefit of a parking cash out or removing parking subsidies depends on the market-rate cost of parking and the current benefits from the employer.

There are other options to reducing drive alone commute shares as well, such as employer office location and the transportation benefits bundle they offer. Rosenfield (2018) examined both of these in two case studies. In the first case study, Partners Healthcare (now called Mass General Brigham) consolidated fourteen offices into one central location in 2016. The previous offices were located around Greater Boston, with some located in Downtown Boston and others located in the suburbs. The new location was adjacent to a new Orange Line subway station: Assembly Row. Parking costs ranged from being free to costing \$480/month for employees in the previous locations. The Assembly Row location charged parking daily at a rate between \$4 and \$10, depending on the income level of the employee. Transit subsidies were 30% before the move (at all locations) and were increased to 50% at Assembly Row. Employee drive alone mode share decreased by as much as 36 percentage points and increased as much as 31 percentage points depending on the previous office location. For example, the previous office locations that were in the suburbs saw the highest drop in drive alone mode shares as the new location was on a subway line. The offices that were previously located downtown, however, had better transit connections than the new location at Assembly Row, and often yielded increases in driving to work.

The second case study examined a pilot between the Massachusetts Institute of Technology (MIT) and the Massachusetts Bay Transportation Authority (MBTA), the transit agency in Greater Boston. The pilot introduced a new program within the corporate program, the Mobility Pass. The Mobility Pass (discussed in more detail in Chapter 5: and 1.1.1A.1Appendix C:) requires all employees at an organization (in this case, MIT) to be covered by a zero marginal cost transit product. MIT, in the pilot, offered fully subsidized bus and subway use to all benefits-eligible employees. However, instead of purchasing a LinkPass for each employee, MIT pays the MBTA on a per-use basis. MIT

previously offered a 50% transit pass discount, which increased to 100% for bus and subway and 60% for commuter rail. They also switched parking costs from annual passes to daily fees (capped at the cost of an annual pass). These changes to their transportation benefits resulted in an increase in transit usage of 10% at a campus that already had a very high transit mode share prior to the new program (Rosenfield, 2018).

Employers have significant leverage in how employees commute to work based on their office location and transportation benefits. Additionally, many employers see transportation benefits as ways to attract top talent and for employee morale and satisfaction. For that reason, employers have historically offered subsidized or free parking. However, this has led to most employees choosing to drive to work, which has caused air pollution and congestion issues in cities and has only worsened climate change. Instead, employers should consider pricing parking and offering transit benefits. However, if they would like to attract top talent and improve employee satisfaction, they could offer a parking cash-out or, as will be discussed further in Chapter 5, a Mobility Pass.

Chapter 3: The Monthly Pass for the Reluctant Commuter Rail Rider

The COVID-19 pandemic caused a massive decrease in transit ridership across the U.S. In the Boston region, the MBTA Data Blog (MBTA, 2021) reported an 80-95% drop in ridership at the beginning of the pandemic stay-at-home directives, depending on mode. As the lockdowns were lifted in the early summer of 2020 and businesses were partially reopening, transit ridership began to rebound. However, as the weather got increasingly colder and infection rates increased in the Fall and Winter, ridership dipped again. Since the stay-at-home orders began in mid-March 2020, transit ridership on the MBTA has never reached levels equal to half of pre-pandemic ridership across any mode.

The commuter rail and ferry systems had the greatest drop in ridership, never surpassing 20% of pre-pandemic ridership in 2020 and often observed around one-tenth of previous levels. The low ridership is mostly due to the type of riders who frequent these modes. They are often higher income passengers and work during traditional work hours (8am - 5pm). The 2015-17 MBTA Passenger Survey (Central Transportation Planning Staff, 2018) found that only around 7% of commuter rail and ferry riders were categorized as low-income. In contrast, about 42% of bus riders and 26% of rapid transit (subway and Green Line) riders were low-income. The survey also found that 90% were making a home-based work trip while 70% of bus and 72% of rapid transit passengers were making those trips. Commuter rail lines have low frequencies as well, with four out of every five stations having less than 9 trains per peak period (i.e., at least a 20-minute headway). When the pandemic hit, higher-income office workers transitioned to a work-from-home environment, drastically reducing their commuting travel. This demographic was most common on the commuter rail and ferry systems, explaining the massive drop in ridership over 2020.

Many commuter rail passengers use the system to avoid traffic and the high parking costs in downtown Boston. When the first stay-at-home order was issued in March 2020, traffic also reduced significantly, especially during the peak hours as people shifted to work-from-home. Many employers who still required some employees to travel to the office offered free or greatly reduced parking. This is partially due to parking lots becoming vacant and partially due to the initial fear that public transit is a high risk for spreading the virus. Thus, it is possible that many commuter rail passengers shifted to driving when traffic dissipated. Only 5% of commuter rail passengers indicated that they did not own a vehicle and over two-thirds have two or more vehicles in their household. For bus riders, 39% indicated they did not have any available vehicles in their household and only one in every five households had two or more vehicles available. Rapid transit passengers were similar to bus riders with 30% without an available vehicle and only 28% with two or more available vehicles at their household. Therefore, when the stay-at-home order began many commuter rail passengers either shifted to driving to work or began working from home, which explains the decline in ridership due to the pandemic.

The drop in ridership is matched with a flattening of the peak curve. The MBTA Data Blog (MBTA, 2021) also reported a sharp shift in time-of-day ridership on the system. Before the pandemic, weekday ridership was sharply peaked around 8 am and 5 pm. In the Fall of 2020 (in the middle of the COVID-19 pandemic), the afternoon peak had flattened to where the ridership at 3 pm was comparable to that at 5 pm. This probably reflects the staggered shifts of “essential” workers, as

they constituted most of the ridership during the pandemic. The drop in peak ridership was proportionally much larger on commuter rail than on the bus or rapid transit systems.

Although ridership is unusually low on commuter rail, it is still possible to gather information on the passenger behaviors to better understand which riders left the commuter rail system and which were still traveling during the pandemic. MBTA commuter rail riders can uniquely purchase tickets on their mobile phones, through a relatively new app, called mTicket, that provides individual, anonymized transaction records for all trips purchased and made on the app. These mTicket data, along with some reasonable assumptions about monthly pass holders and single ticket purchasers, allows one to develop rider segments based on frequency and day-of-week use of commuter rail.

The first section (Section 3.1 Commuter Rail Fare Products Overview) describes the mTicket fare products currently offered. The next section (Section 3.23.2) discusses the mTicket data availability and compares mTicket riders to commuter rail users overall. Given that mTicket captures a different market than commuter rail overall, the following section (Section 3.33.3) discusses the methodology used to scale mTicket data to reflect overall commuter rail ridership and revenue. To understand how passengers have been impacted by the COVID-19 pandemic, this chapter uses k-means clustering, an unsupervised machine learning algorithm, to segment commuter rail passengers by similar travel behaviors. Section 3.43.4 explains the segmentation methodology used to classify mTicket riders and the application of those results along with additional data assumptions to classify overall commuter rail ridership segments prior to the pandemic. These pre-pandemic segments are then compared to data from Fall 2020 that uses the same segmentation procedure to understand which segments were more likely to stay in the system and which stopped riding during the pandemic (Section 3.5).

The MBTA, in an effort to match a product to the new passenger behaviors, introduced the “Flex Pass,” a new fare product created during the pandemic to offer flexibility for frequent and occasional riders who may be uncertain if they will ride enough to justify the cost of a monthly pass (Section 3.6). Section 3.7 analyzes the Flex Pass take-up and user behaviors compared to other passes, including some inferences on which rider segments have primarily adopted this new commuter rail fare product. Section 3.8 then explores how alternative designs of the Flex Pass may help attract ridership back to the MBTA system using various ridership return scenarios. Of these, the 20/30 product fared greatest at capturing ridership and matching user preferences. The final section (Section 3.9) discusses the results from this chapter and potential implications as the pandemic is expected to subside with vaccine roll-out throughout 2021.

3.1 Commuter Rail Fare Products Overview

The MBTA commuter rail system does not generally accommodate passive data collection through its fare collection system except for a single sales channel. The most common sale channels are from fare vending machines (FVMs) or sales offices for paper tickets, through Perq for Monthly Passes on Charlie Cards (the plastic card used on the bus and subway system), onboard tickets purchased from conductors, or through the mTicket mobile app. Paper tickets (typically purchased at FVMs or sales offices) are shown and clipped by conductors, who walk up and down the aisles during the train ride. Monthly passes through the Perq program are called “Flash Passes” for commuter rail. The Flash Pass is a Charlie Card that can be used on the bus and subway system with a tag indicating it can be used up to a certain zonal fare on commuter rail. Users show, or “flash”, the pass to conductors to validate it. Flash Pass users get a new card each month to prevent fare evasion. On-board fare collection involves purchasing a ticket from a conductor and receiving a paper One Way

or Round Trip ticket, which is immediately validated by the conductor. Finally, the mTicket app allows users to purchase tickets from the app and activate them so they can be validated visually by conductors.

The mTicket app operates distinctly from much of the MBTA fare collection system. The app allows users to purchase a ticket and “activate” it to validate their fare. Since the commuter rail system does not have faregates¹, users have to show train conductors their fares to validate their trips. There are two types of fare products on mTicket: individual tickets and passes. To activate individual tickets (One Way, Round Trip, or 10 Ride), the user clicks the ticket and hits the “Activate Ticket” button on the screen. The activated ticket lasts 90 minutes and shows a colorful banner (gray when inactive or used) for the conductor to know the ticket is valid (see Figure 3-1). Activations on passes occur whenever the activated ticket is opened in the app by the user. These two forms of activation have implications on the data collection and the purchase behavior of users. Since the individual tickets have to be validated by train conductors, users sometimes avoid paying a fare when the conductors do not check fares. While train conductors are required to make rounds across the aisles to collect fares, there are instances in which they skip a round or, as occasionally occurred before the pandemic, the trains were over-crowded and conductors were unable to check everyone’s tickets before they alighted. The exact number of fare evaded trips that occur on commuter rail is unknown to the agency. Since period passes are purchased once and can be used without limit for a specified period after it is activated, the issue of fare evasion is not as likely. This is especially true with Monthly Passes, which are based on calendar months.

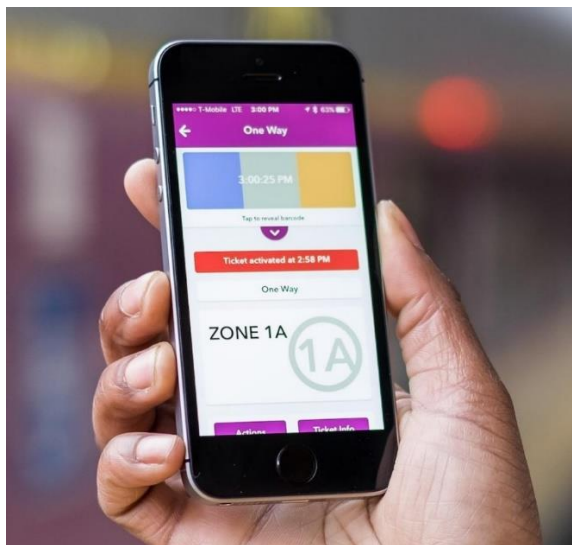


Figure 3-1: An mTicket ticket showing the colored banner above, indicating it is activated

mTicket offers six fare products: One Way, Round Trip, Ten Ride, Monthly Pass, Weekend Pass, and Flex Pass (new since July 2020). The first three are pay-as-you-go (PAYG) tickets while the last three are pass products. In Fiscal Year 2019 (see Figure 3-2), there were 925,000 activations made each month on average. Of those, 28% came from One Way tickets, 21% from Round Trip, 24% from 10 Ride, 23% from Monthly Passes and 3% from Weekend Passes. This is very similar to the

¹Part of the AFC 2.0 plan is to introduce faregates at core stations on commuter rail, such as North Station, South Station, and Back Bay. These were not permanently in place during the research analysis.

revenue distribution for each product during the same time period, which makes sense as revenue and ridership often go hand-in-hand (but not always).

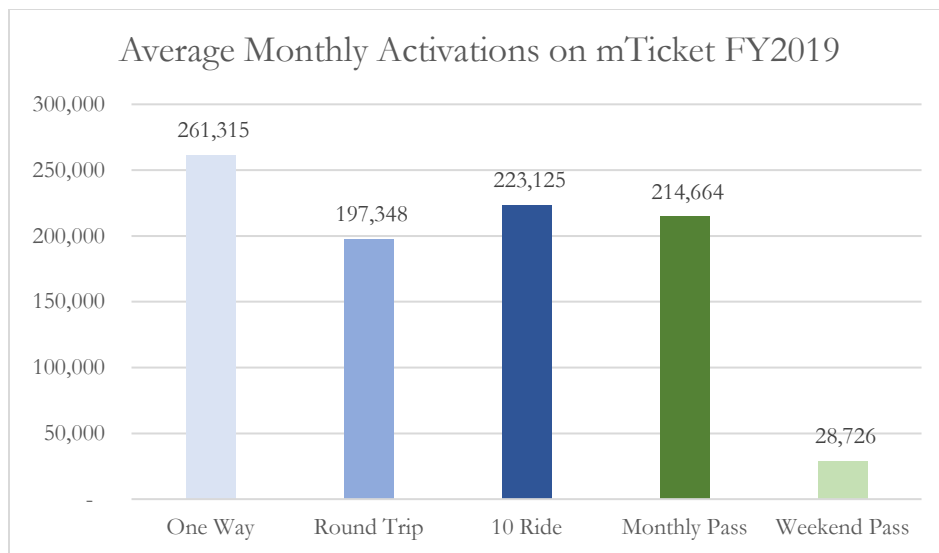


Figure 3-2: Average Monthly Activations on mTicket for Fiscal Year 2019

Trip distributions across all fares on commuter rail are different from mTicket’s distribution. Section 3.2 goes into further detail on the differences between PAYG tickets and passes on the entire commuter rail network. An important consideration throughout this analysis is that mTicket primarily sells PAYG tickets while other sale channels, especially the Perq program, sell most of the pass products. The one exception is the Flex Pass, which is only available on mTicket (more on that in Section 3.5). Throughout this analysis the volume and percent of ridership (i.e., one-way passenger trips) and users (individual “unique” passengers as defined by their account ID) are illustrated. These two terms are not interchangeable, although the terms users and riders are used interchangeably. Ridership refers to the total trips taken, regardless if taken by the same person or different people. Users are the individual persons who interact with the commuter rail system. As will be shown in subsequent analyses, roughly half of all commuter rail users account for 90% of the ridership on the system. This highlights the importance of distinguishing between the two terms.

3.2 Using mTicket as Commuter Rail Passenger Behavior Proxy

While the MBTA bus and subway systems have Automated Fare Collection (AFC) and Automatic Passenger Count (APC) systems that collect data on passenger volumes, commuter rail does not have a system-wide method to collect ridership data. Commuter rail and ferry (henceforth collectively called “commuter rail” unless otherwise separated) fare collection is performed by train conductors who visually validate tickets. Since fare validation is done manually, the only way to collect ridership data on commuter rail is through manual counts (usually done at core stations – i.e. North Station, South Station, etc.) or through an analysis of stored mTicket transactions.

Manual counts only capture the volume of riders on a line, making it difficult to understand origin-destination (OD) flows on the system. However, the mTicket app is able to capture richer, more granular data on ridership. Purchases and ticket validations can be linked to user accounts, allowing

for disaggregate data analysis. Ticket validations on mTicket are recorded when the user activates their ticket (etiquette is to activate it before boarding the train). Since a pass user might open the ticket multiple times during a trip, only activations that were at least 90 minutes apart were considered in this research study.

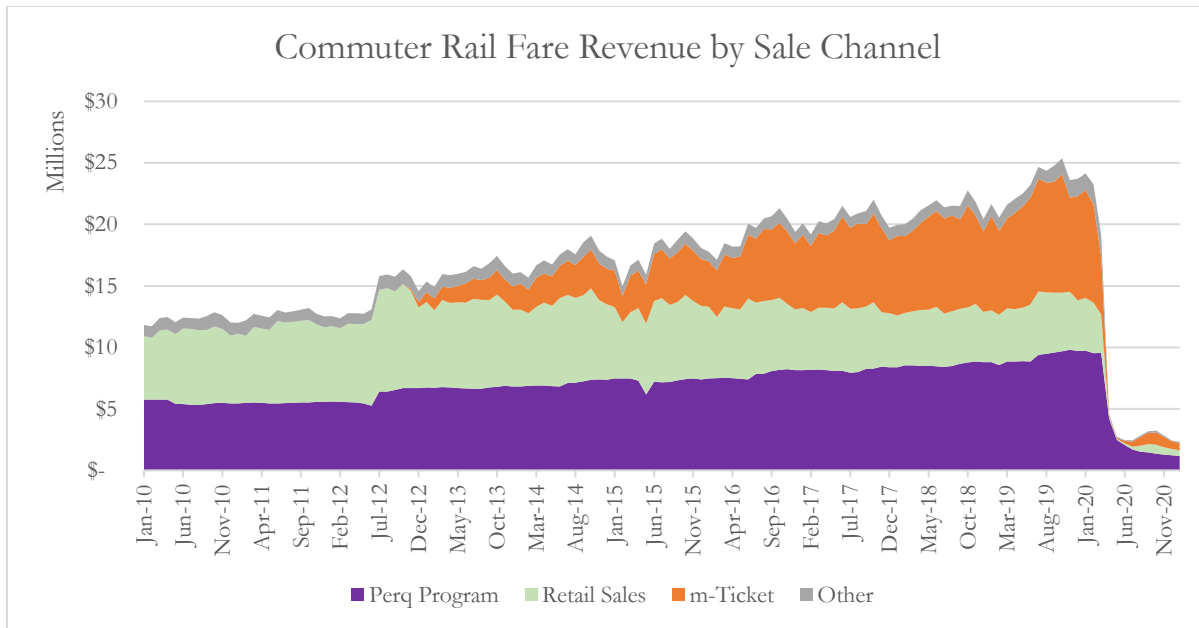


Figure 3-3: Commuter rail and ferry fare revenue by sale channel. mTicket was rolled out at the end of 2012 and has since overtaken retail sales as the second largest sale channel.

mTicket adoption has increased steadily over the past few years. Figure 3-3 shows the fare revenue on commuter rail by sale channel. Since 2013, mTicket revenue has been gradually increasing, eventually overtaking Retail Sales as the second largest sale channel distribution behind the Perq Program. As is shown in Figure 3-3, and as will be discussed further in subsequent sections, the COVID-19 pandemic led to a significant decline in commuter rail ridership (and, therefore, revenue). While revenue, prior to March 2020, was steadily increasing since 2010, ridership has not matched this increase. Instead, multiple fare increases have occurred since 2012 which have led to increased fare revenue. Figure 3-4 illustrates the decline in ridership on the MBTA bus, subway, and commuter rail systems from 2013 to 2019 based on unlinked trips. Data for this chart was pulled from the National Transit Database (Transit Agency Profiles, n.d.), which collects annual reports from transit agencies across the United States. Commuter rail ridership experienced a decline from a peak of 36.6 million unlinked trips in 2014 to 32.8 million trips in 2019, a 10% drop in the 5-year span.

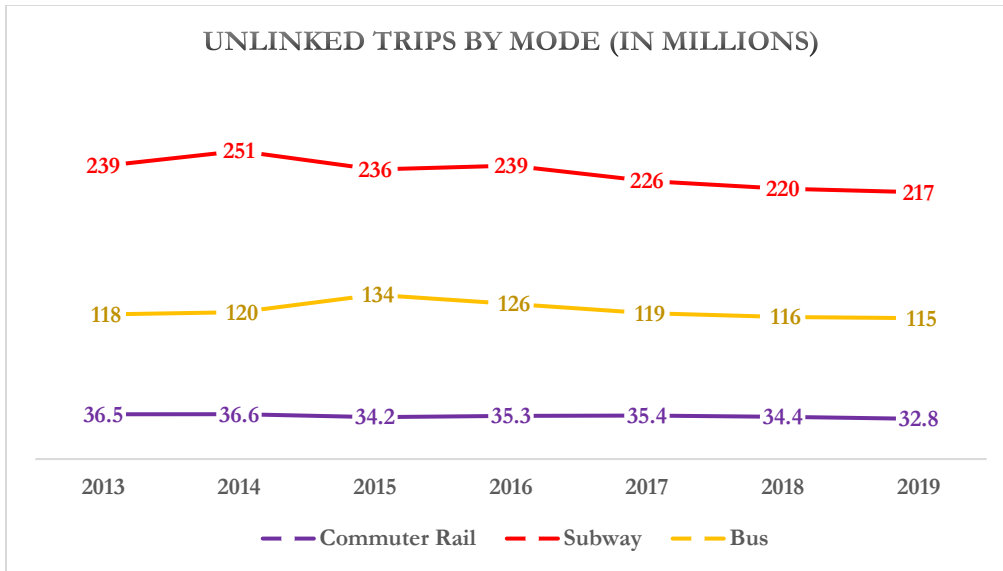


Figure 3-4: Unlinked Trips by Mode on the MBTA from 2013 to 2019 (National Transit Database)

Nonetheless, mTicket ridership has continued to grow as the app has attracted users from the retail sale channel. The number of accounts using mTicket has increased over the past few years. While there are seasonal variations in the number of unique accounts used each month, there is a general increase from roughly 80,000 unique accounts in October 2016 to over 140,000 in the summer of 2019 (see Figure 3-5). This high volume of users and large proportion of revenue provides a rich dataset for detailed commuter rail analyses. For those reasons, it is used in this research to analyze disaggregate ridership behaviors.

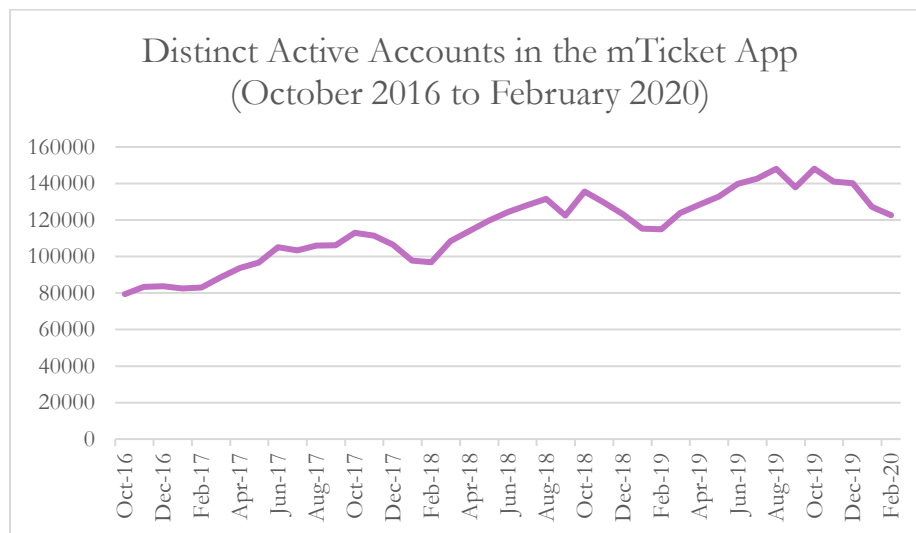


Figure 3-5: Number of unique active accounts on mTicket between October 2016 and February 2020

3.3 mTicket Scaling

While mTicket provides a richer dataset than manual counts, it still only constitutes a little over one-third of the overall commuter rail population. As previously mentioned, detailed overall commuter rail ridership is rare. In order to understand travel behaviors across the commuter rail system rather

than just mTicket, a scaling methodology is applied to the mTicket results. There are various resources available that help understand the proportion of mTicket users on commuter rail. These include the 2015-17 MBTA System Passenger Survey, the 2018 Commuter Rail Counts (Central Transportation Planning Staff, n.d.), and accounting data for Fiscal Year 2019. Given that the proportion of mTicket users has increased over time (see Figure 3-6), this analysis uses a fare product breakdown from Fiscal Year 2019 to estimate overall commuter rail ridership. While Fiscal Year 2020 data could have been used, the drastic revenue impacts from the COVID-19 pandemic provides uncertainty in the scaling. For example, the spike in the proportion of Perq Program revenue between April and July 2020 is partially from auto-renewal of commuter rail passes as well as commuter rail conductors not validating fares during this period (for safety reasons, similar to the rear-door boarding policy on buses). Thus, Perq passes were still being purchased (albeit at a much lower rate) while Retail and mTicket sales were near-zero until fare collection was reinstated in late-July 2020.

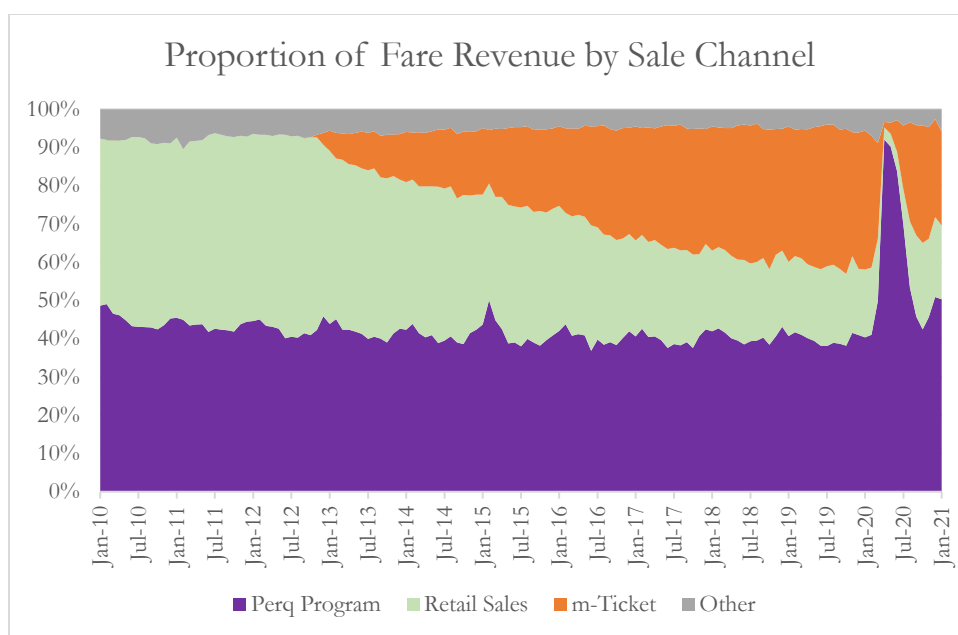


Figure 3-6: Proportion of Commuter Rail Fare Revenue by Sale Channel (2010 to 2021)

As previously mentioned, the scaling methodology to estimate overall commuter rail ridership from mTicket data is based on the accounting data for Fiscal Year 2019. Table 3-1 shows the revenue for Fiscal Year 2019 broken down by sale channel distribution (rows) and fare product (columns). Weekend passes, which began as a pilot in the summer of 2018, are not included in the accounting data but only constitute a small portion of overall revenue. Overall, mTicket represented 34.5% of commuter rail revenue. However, it was only 13% of monthly pass sales while accounting for 70% of pay-as-you-go sales (e.g. One Way, Round Trip, and 10 Ride). The bulk of monthly passes are from the Perq program (formerly Corporate Program). This is partially due to the ability to transfer to bus and subway with a physical monthly pass (no transfers on mTicket) and also because the Perq program only offers monthly passes².

² The Corporate Program (Perq) shows revenue on the 10 Ride tickets. This is from reduced fare users, which are unable to purchase a Monthly Passes and are offered 10 Ride tickets instead.

Table 3-1: Commuter rail revenue in Fiscal Year 2019 by sale distribution channel (rows) and fare product (columns)

FY 2019	Monthly Pass	One Way	Round Trip	10 Ride	Other	Total	Percent
Corporate Program	\$ 100,876,468	\$ -	\$ -	\$ 179,341	\$ -	\$ 101,055,809	39.9%
FVM Sales	\$ 7,219,311	\$ 2,011,370	\$ 1,664,612	\$ 181,887	\$ -	\$ 11,077,179	4.4%
Keolis Conductor	\$ 144,975	\$ -	\$ 13,841,817	\$ 9,120	\$ 298,554	\$ 14,294,465	5.7%
Keolis Sales Office	\$ 18,483,167	\$ 2,749,391	\$ 4,386,482	\$ 1,274,260	\$ -	\$ 26,893,300	10.6%
mTicket	\$ 21,010,462	\$ 24,998,744	\$ 20,345,072	\$ 20,794,674	\$ -	\$ 87,148,952	34.5%
Other	\$ 9,947,302	\$ 565,968	\$ 1,885,657	\$ 97,995	\$ -	\$ 12,496,922	4.9%
Total	\$ 157,681,684	\$ 30,325,473	\$ 42,123,639	\$ 22,537,277	\$ 298,554	\$ 252,966,626	100.0%
Percent	62.3%	12.0%	16.7%	8.9%	0.1%	100.0%	

Scaling, therefore, should be based on the pass purchasing behavior of the users. The scaling process takes the total revenue per product and divides it by the share of mTicket sales for that product. This value is the scaling factor that will be used to scale the mTicket results up to the overall commuter rail ridership. For example, the total sale of monthly passes in the commuter rail system was \$157.7 million, of which \$21 million came from mTicket. The scaling factor for monthly pass purchasers from mTicket would be:

$$\begin{aligned} \text{ScalingFactor} &= \text{MonthlySales}_{CR} / \text{MonthlySales}_{mtix} \\ \text{ScalingFactor} &= 157.7 / 21 \\ \text{ScalingFactor} &= 7.5 \end{aligned}$$

The scaling factor is applied to monthly average user profiles, which aggregate all trips taken per account per month. The most commonly used fare product for each rider profile is used to categorize the user by fare product so a scaling factor can be applied. This is done as only 17.5% of mTicket users have purchased more than one product type in January 2020. Of those who purchased more than one product, the vast majority were purchasing two different types of pay-as-you-go tickets, such as a One Way and Round Trip ticket. For that reason, it is assumed that the product purchased per user is the one they used the most. This scaling methodology provides an estimate of the overall commuter rail individual user population and can be applied to the following clustering analysis to understand the proportion of users and ridership for each cluster.

3.4 mTicket Clustering

The goal of this research analysis is to understand what types of riders stopped traveling on commuter rail during the COVID-19 pandemic and how the behavior shifted from those who were still traveling. Knowing how ridership patterns shifted during the pandemic helps understand which riders are missing and how they might be incentivized to return. The MBTA created the Flex Pass in the summer of 2020 as a fare product that would better serve the riders who left the system during the pandemic. However, they created this fare product without a thorough analysis of the ridership pattern shifts. This section analyzes the commuter rail ridership prior to the COVID-19 pandemic and Section 3.5 explores the pattern shifts due to the stay-at-home orders; both sections use a clustering algorithm to segment the users to better understand pattern shifts.

Clustering algorithms are useful tools to segmenting a population by similar user behaviors. The population segments can then be used to understand ridership changes based on fare increases or external events. There are many clustering algorithms, yet the simplest, and the one used in this thesis, is K-means clustering. K-means is an unsupervised machine learning algorithm that uses the Euclidean distance between data points to separate the data into clusters. The hyperparameters of the algorithm are the number of clusters (k) and the feature set. Details on the methodology for

choosing the number of clusters (k) and feature set can be found in Appendix A: The clustering methodology was applied to pre-pandemic ridership from January 2020 (full month). All ridership data was aggregated by month to match the calendar-based Monthly Pass.

After testing the hyperparameters and analyzing the results, the data was split into two groups, single-day and multi-day riders, of which there are four clusters from the single-day riders and six clusters from the multi-day riders. Single-day riders constituted 43.4% of mTicket users in January 2020 but only 8.3% of all trips taken. Since these riders were only on the system one day, their clustering behavior was clear-cut. The only two features that distinguished these users was percent of their trips taken during the peak (*peak_n*) and percent of their trips taken on the weekend (*weekend_n*). Figure 3-7 is a heatmap of each single-day mTicket user's behavior in January 2020. Each horizontal line on the figure represents one single-day user, with the percent peak and percent weekend trips shaded by the ridership behavior. For example, the cluster on the top has all users with 0% of their trips during the peak and 100% of their trips taken on the weekend. The size of the *cluster_label* column represents the number of users that are categorized in that cluster within the Single-day cluster. Note that the size of the clusters depicted is not scaled, but the percent on the label is scaled using the methods described in Section 3.3. From this heatmap, there are four clear clusters that are formed: Weekend, Peak, Off-Peak, and Half-Peak. These cluster labels describe the type of behavior experienced by each user.

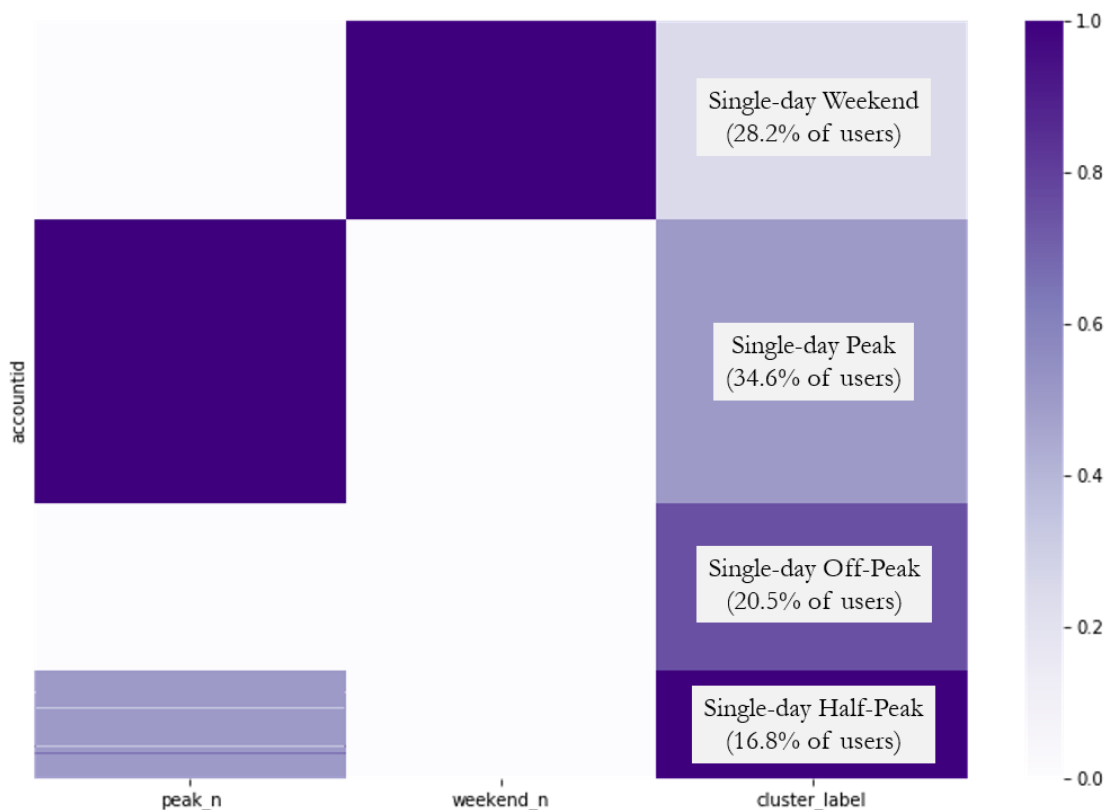


Figure 3-7: Heatmap of mTicket Single-day user's travel behavior in January 2020

Multi-day riders are defined by the number of unique days they traveled normalized to all possible days traveled (*active_days_n*), percent of their trips taken during a peak hour (*peak_n*), percent of their trips taken on the weekend (*weekend_n*), and the range of their days traveled normalized by the

longest possible range (last day - first day, *range_n*). Figure 3-8 shows a heatmap of multi-day riders for each feature (active days, peak, weekend, and range). As with the single-day users, each horizontal line (more distinguishable on this graph) is one mTicket account ID, shaded by their travel behavior for each feature. The Occasional Peak cluster has a moderate number of active days traveled, a high percent of their trips during the peak, low percent during the weekend, and a fairly high range of travel. These users have an occasional ridership (based on the moderate number of active days traveled) and almost always ride during the peak hour, thus defining its label. The cluster labels for these riders are shown in the *cluster_label* column. Note that the heatmap is not scaled to overall commuter rail ridership, but the percent of users indicated on the cluster label is scaled.

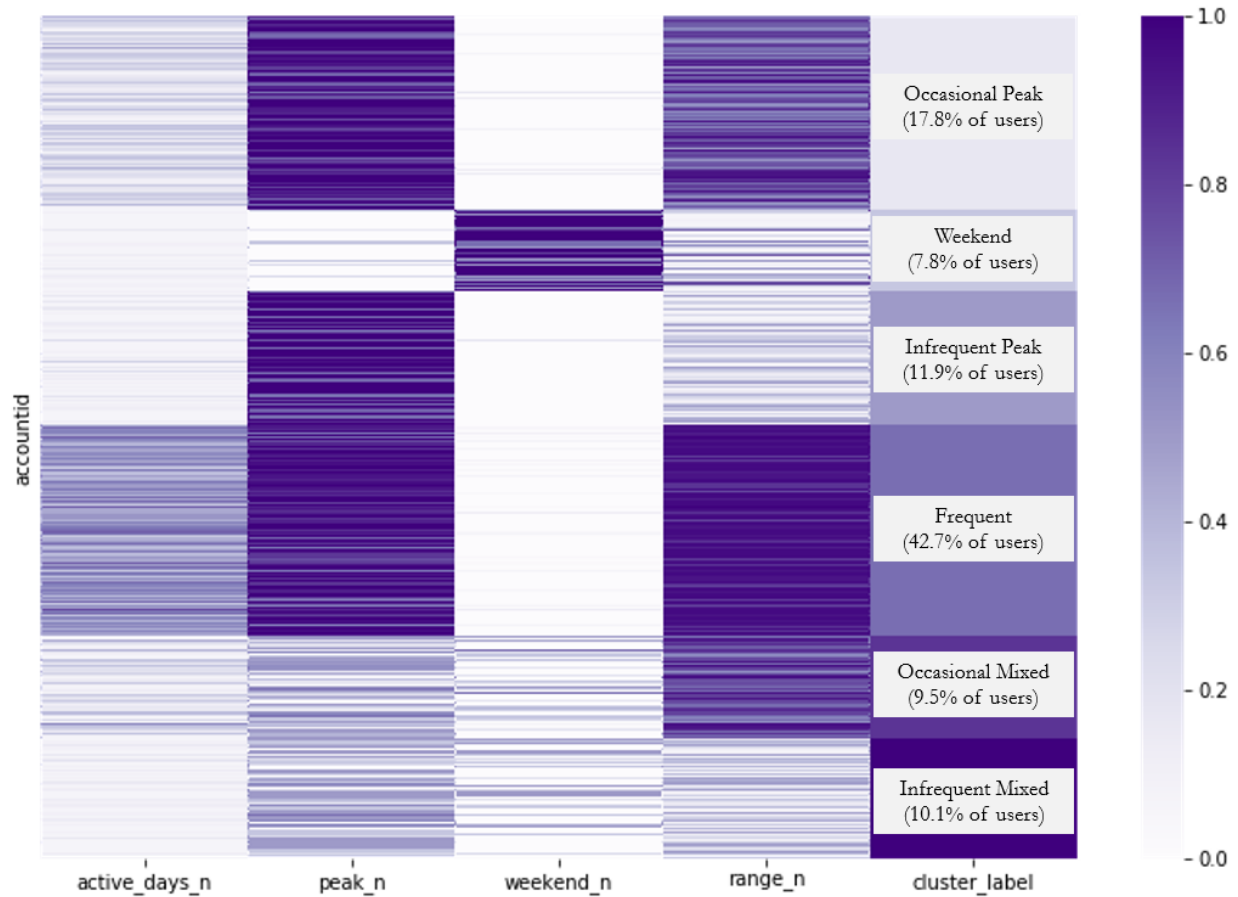


Figure 3-8: Heatmap of mTicket Multi-day users' travel behavior in January 2020

Taken together, there are ten clusters in the analysis. Figure 3-9 shows the distributions of the four features within each cluster. Note that none of the single-day clusters used the *active_days_n* or *range_n* features, since, by definition, they all rode one day with a range of zero. The clusters are separated by frequency of travel and time of usage. Figure 3-9 shows how the Frequent cluster has the highest active days and range compared to the other clusters. They also happen to mostly travel during the peak, which suggests they are traditional commuters who travel during the morning and evening peak hours. The two “occasional” clusters have similar active days and range distributions but differ on what how much they ride during the peak hours. The “infrequent” and “weekend” clusters have the lowest active days and range of the multi-day clusters but differ depending on if they travel during the peak hours or weekend.

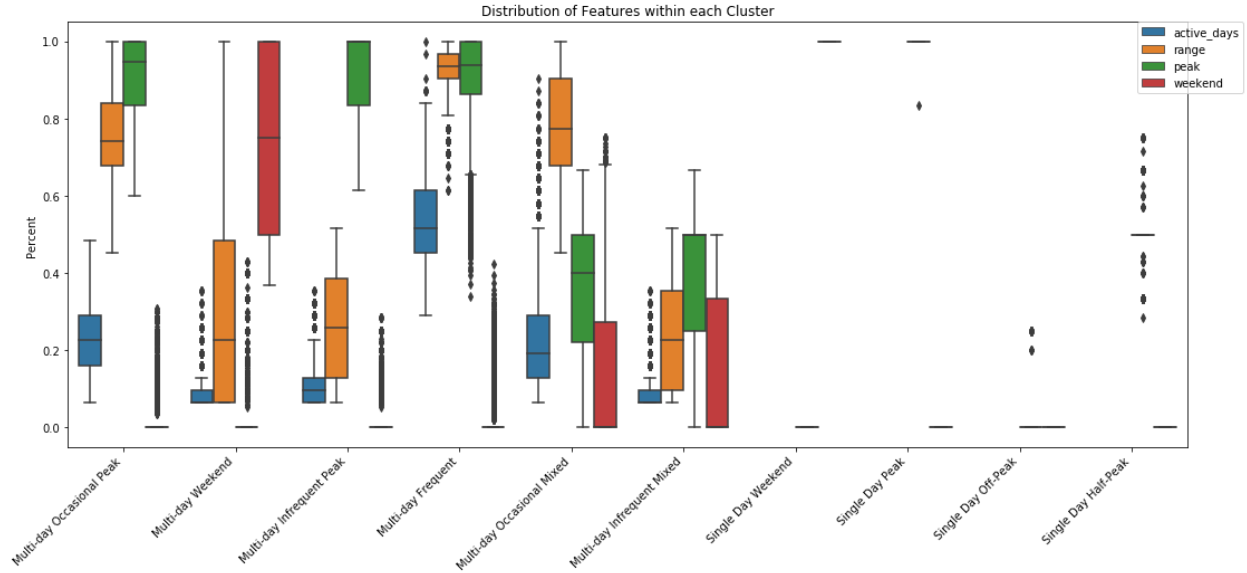


Figure 3-9: Distribution of mTicket users in each cluster by feature. Single-day features often appear as a flat line, indicating no variability in the feature.

After classifying the users by cluster, the clusters are scaled up to an estimated overall ridership using the scaling method discussed in Section 3.3. The scaled data gives an estimate for the overall commuter rail rider behaviors. Figure 3-10 shows the estimated breakdown of each cluster by the sale channel used to purchase fare products. As discussed in the scaling methodology, the Perq Program is the largest distributor of monthly passes on the commuter rail system. This explains the significant portion of users who purchase their products through Perq in the Multi-day Frequent cluster. Additionally, retail is the next largest distributor for PAYG tickets, outside of mTicket, and captures large portions of the remaining clusters along with mTicket.

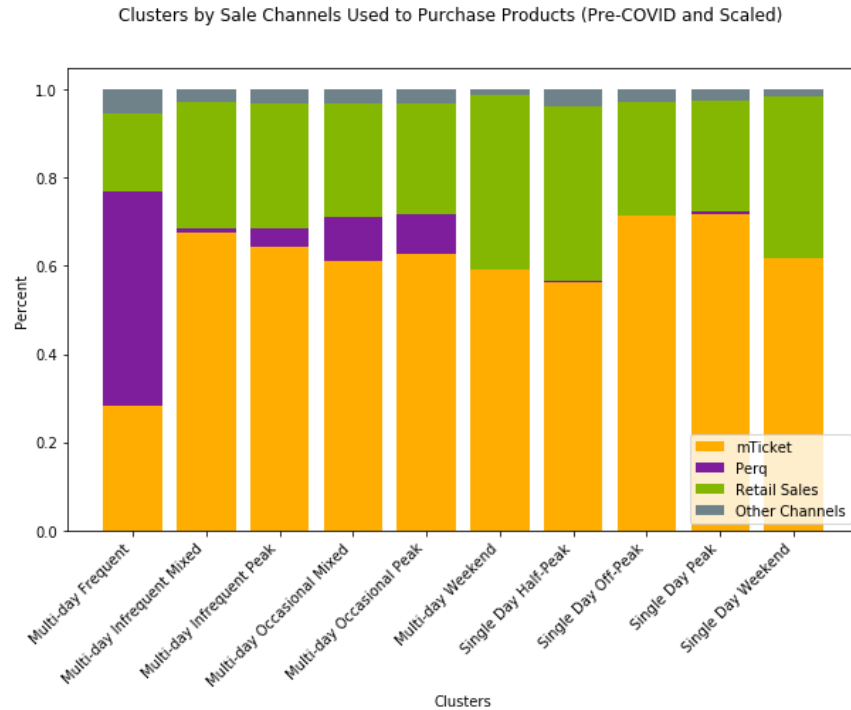


Figure 3-10: Clusters by the estimated sale channel used to purchase the fare product (pre-pandemic and scaled)

Table 3-2 shows the estimated trips taken and number of unique users for each cluster on the commuter rail system. These values are scaled to the overall commuter rail system using the scaling procedure from Section 3.3. The Multi-day Frequent cluster is by far the most active cluster as they represented over two million trips in January 2020, or 71% of all trips taken on commuter rail in that month. Less than three out of every ten riders are considered Multi-day Frequent, indicating consistency in their ridership behaviors. Given that nearly half of the Multi-day Frequent cluster purchases their fare products through Perq, it follows that nearly 40% of the fare revenue is from the Perq Program.

All of the Single-day, Infrequent, and Weekend clusters accounted for a little over half (55%) of the users who interacted with the commuter rail system in January 2020. However, their trips on the system only constituted 11% of all trips that month. This distinction is important for transit agencies. On one hand, it is useful to target the frequent and occasional riders since they are consistent users and constantly interact with the system. On the other hand, half of all unique people who travel on commuter rail are infrequent riders with the potential to increase their ridership. Transit agencies should look to maintain frequent and occasional riders while encouraging infrequent riders to increase their usage on the system.

Table 3-2: Cluster breakdown by number of trips and users and the proportion of trips and users from each cluster (pre-pandemic and scaled)

Cluster	Trips	% Trips	Users	% Users
Multi-day Frequent	2,027,776	70.8%	63,585	27.4%
Multi-day Infrequent Mixed	58,406	2.0%	15,068	6.5%
Multi-day Infrequent Peak	94,805	3.3%	17,756	7.7%

Multi-day Occasional Mixed	180,474	6.3%	14,208	6.1%
Multi-day Occasional Peak	328,414	11.5%	26,509	11.4%
Multi-day Weekend	40,603	1.4%	11,679	5.0%
Single-day Half-Peak	32,212	1.1%	13,896	6.0%
Single-day Off-Peak	23,841	0.8%	16,979	7.3%
Single-day Peak	37,105	1.3%	28,656	12.4%
Single-day Weekend	38,479	1.3%	23,404	10.1%

Users in each cluster likely purchase different fare products to match their ridership patterns. Monthly passes, for example, are cost effective for people who travel more than 16 days per month. The pass multiple, or the number of trips needed for someone to break-even on their purchase, for monthly passes is roughly 32 trips per month. This varies by the zone, as each zone has a different fare. For people who work five days a week, they would travel between 20 and 23 days per month, or 40 to 46 trips if they travel to and from work each of those days, depending on the number of weekdays in that month. Monthly passes are attractive for transit agencies as well, as they are a sunk cost but provide zero marginal cost to the user. This means that once a rider purchases a monthly pass, they are invested in reaching the pass multiple (to “get their money’s worth”) and have a lower barrier to use transit more often than they otherwise would have. If a frequent user forgoes the monthly pass and instead purchases pay-as-you-go tickets for each trip, they are conscious of spending the fare for each trip. Behavioral science research suggests that the salience of paying a fare, that is, the amount someone is actively aware they are spending money, affects their purchase behavior. Credit cards are an example of a low salient fare medium. People are more likely to spend money through a credit card than with cash since the transaction amount on a credit card is obscured and not felt until the monthly bill arrives, whereas people are more aware of the cost of an object as they purchase it with cash. A monthly pass works in a similar way, where the cost of the pass is felt once up front, but each additional trip is essentially free (zero marginal cost). Purchasing individual pay-as-you-go tickets means potentially forgoing trips on transit since you would have to pay the fare of the ticket for each additional trip.

However, not everyone benefits from a monthly pass. People who have multiple modes to get to work (i.e. driving and commuter rail) might not make 32 trips per month to reach the pass multiple. Additionally, not all work shifts are five days a week. Many jobs, such as nurses, work three or four days a week. Even if they travel strictly on commuter rail, they would not reach the pass multiple on work days alone. For those reasons, many commuters are better off purchasing pay-as-you-go tickets. The decision to purchase a One Way, Round Trip, or 10 Ride ticket is mostly arbitrary, as there is no discount on a Round Trip or 10 Ride ticket (2 One Way tickets = 1 Round Trip ticket, 10 One Way tickets = 1 10 Ride ticket). However, the tickets have a 90-day expiration, so a user would have to ride ten times in a 90-day span to get the full value of a 10 Ride ticket. The benefit to purchasing a 10 Ride or Round Trip ticket over a One Way ticket is convenience of not having to go through making the transaction each time you take a trip.

As each user would benefit from a different fare product, we would expect the clusters to reflect the product preferences of the users. Figure 3-11 shows the most commonly used fare product by each user by their cluster. As expected, the Multi-day Frequent cluster predominantly purchased monthly passes with only a quarter preferring another product. The Occasional groups had a few monthly pass users, despite lower trips taken on average. Interestingly, 6.5% of Infrequent Peak users preferred a monthly pass while only 1.4% of Infrequent Mixed users did the same. However,

commuter ticket validation occurs when a user opens the mTicket app and shows the conductor their pass. It is possible that a conductor would skip the formal validation of a ticket (visually inspecting the ticket on the phone) if they know the passenger and have seen their monthly pass earlier. It is unclear if these monthly pass Infrequent users are riding infrequently or if their data is not being collected properly. Note that riders who prefer 10 Ride tickets follow similar patterns as monthly passholders, primarily being frequent, occasional, or peak riders.

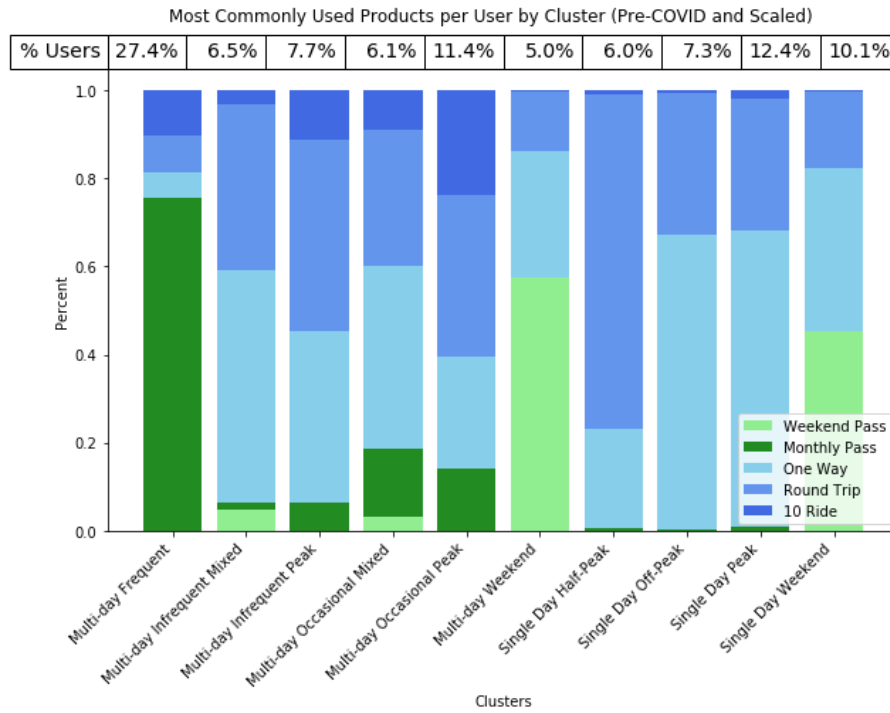


Figure 3-11: Most common fare product used by riders in each cluster (pre-pandemic and scaled). The most common fare product is determined by the number of activations (i.e. trips) by each user. The top bar shows the proportion of all users within each cluster.

One pass not mentioned much before is the \$10 Weekend Pass. This pass (often called the “Weekend Pass”) offers free travel to all zones on the weekend for just \$10. For any zone further than 1A (Zones 1 to 10), the Weekend Pass is cheaper than a Round Trip ticket to the same location when used on the weekend. Interzones, however, are cheaper between Interzone 1 and 5 than the Weekend Pass. Interzones are not often purchased since the commuter rail system is radial with few transfers outside of Zone 1A. For the Single-day Weekend cluster, it would be expected that a much higher proportion of the users would use a Weekend Pass since they only used the system on one day on the weekend. It is possible that some of the One Way product users only took a single trip on the weekend, thus making it cheaper to purchase a One Way ticket rather than a Weekend Pass. However, it is likely that most of the One Way and Round Trip users in the Single-day Weekend cluster spent more money on their trip than had they used a Weekend Pass. This might be due to uninformed users who were not familiar with the Weekend Pass, which was made permanent in 2019.

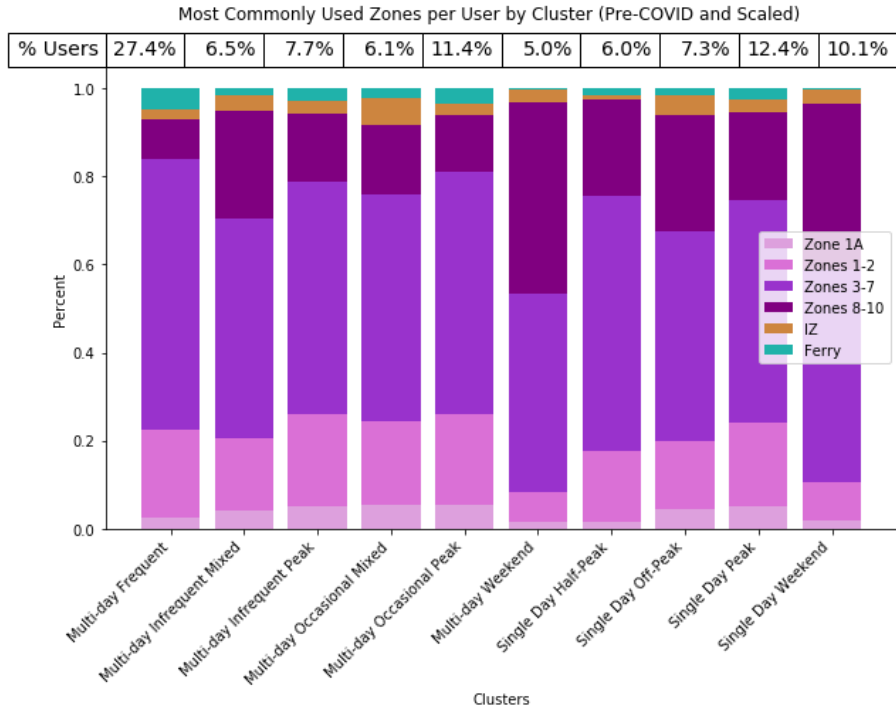


Figure 3-12: Most common zone traveled to/from central Boston (Zone 1A) by riders in each cluster (pre-pandemic and scaled). The most common zone is determined by the number of activations (i.e. trips) by each user. The top bar shows the proportion of all users within each cluster.

Besides fare products, it is useful to check what zones users travel to or from. For the most part, there should not be much distinction between clusters for the zones they travel. However, Figure 3-12 shows how the Weekend clusters have a much higher proportion of the outermost zones compared to frequent and occasional clusters. This makes sense, as the outermost zones are often tourist destinations that people like to visit on the weekends, such as Rockport, Newburyport, Plymouth, Worcester, Wachusett, and Providence, Rhode Island. The intermediate zones, Zones 3-7, are more residential than the outermost zones and therefore more utilized by frequent commuters. Zone 1A parallels much of the MBTA subway system in the core of the city, so occasional and infrequent users might switch between commuter rail and other rapid transit, depending on which is more convenient on a particular day.

The K-means clustering analysis segments commuter rail riders by travel behaviors and shows the distribution of these users on the system. Seven out of ten trips are taken by frequent riders, who represent just over a quarter of all people who interact with the commuter rail system each month. This group of frequent riders dominates the ridership on the system and, as is discussed in Section 3.5, is a key reason why ridership declined during the COVID-19 pandemic. In addition, the frequent, occasional, and peak users have similar fare product preferences as they are the most likely to purchase Monthly passes or 10 Ride tickets. Finally, roughly half of all people who use the commuter rail system account for around 90% of all trips. This creates an opportunity for transit agencies to increase ridership among the half of users who occasionally take trips while maintaining the ridership among the frequent users.

3.5 Changes to Clusters due to COVID-19

This section looks at the shift in ridership by cluster due to the pandemic. The pre-pandemic analysis (Section 3.4) uses ridership data from January 2020, shortly before the pandemic, while the “during pandemic” analysis (this section) uses data from October 2020, in the midst of the pandemic on a historically high ridership month. In October 2020, mTicket ridership was about 12% of pre-pandemic levels. However, there were still enough interactions to be able to find trends in the two datasets.

The users from the month of October were segmented into specific clusters based on assigning each user to the closest centroid from the clusters created from the K-means clustering algorithm for January 2020. Each user in October was matched with the nearest centroid from the January 2020 analysis using the Euclidean distance. This preserves the clusters from before the pandemic and allows for a direct comparison of ridership changes within each cluster. Table 3-3 shows the percent of trips and users in each cluster in October 2020 (during the pandemic) compared to January 2020 (pre-pandemic). Notably, the Multi-day Frequent cluster, which constituted 71% of ridership in January 2020, has less than 5% of the ridership it had pre-pandemic. Despite ridership being at 12% of pre-pandemic levels on mTicket, the Single-day Weekend cluster has roughly half of the ridership as it had before the pandemic. Relatively high Single-day, Weekend, and Infrequent cluster retention (compared to the overall system) suggests that commuter rail trips for non-work purposes have continued or are beginning to return at a faster rate than commuting trips. This is noticeable with the two Weekend clusters, which have ridership levels at 41.5% and 52.7% of the pre-pandemic baseline.

Table 3-3: Percent of ridership and users in October 2020 compared to January 2020 (pre-pandemic baseline, scaled)

Cluster	% Trips from Baseline	Baseline Trips	% Users from Baseline	Baseline Users
Multi-day Frequent	4.3%	2,027,776	4.8%	63,585
Multi-day Infrequent Mixed	19.7%	58,406	22.8%	15,068
Multi-day Infrequent Peak	11.7%	94,805	13.9%	17,756
Multi-day Occasional Mixed	20.1%	180,474	26.2%	14,208
Multi-day Occasional Peak	8.6%	328,414	11.6%	26,509
Multi-day Weekend	41.5%	40,603	41.1%	11,679
Single-day Half-Peak	16.0%	32,212	15.9%	13,896
Single-day Off-Peak	29.6%	23,841	31.0%	16,979
Single-day Peak	18.1%	37,105	18.8%	28,656
Single-day Weekend	52.7%	38,479	50.4%	23,404

The drop in ridership across clusters is higher among Frequent, Occasional, and Peak clusters, the same which were most likely to purchase monthly passes or 10 Ride tickets. Between the two Infrequent and Occasional clusters, the Peak cluster (Infrequent Peak and Occasional Peak) had much lower trip retention than the Mixed clusters (Infrequent Mixed and Occasional Mixed). The Occasional Peak cluster had 11.5-percentage points lower trip retention than the Occasional Mixed cluster and the Infrequent Peak cluster had 8.0-percentage points lower trip retention than the Infrequent Mixed cluster. This suggests that the riders most likely to stop taking commuter rail are

the ones with traditional work hours who travel during the peak. This matches the understanding of who was traveling during the pandemic – mostly healthcare and shift workers – who do not have traditional working hours and might work three or four days a week rather than Monday through Friday.

Not only have the frequent, occasional, and peak clusters had the largest decline in trips and users due to the pandemic, but Figure 3-13 shows a decrease in the distribution of total trips among these clusters. The average number of trips taken for all Multi-day clusters, except for the Multi-day Weekend cluster, declined by at least 13%. While users are still categorized in these clusters based on their ridership patterns, the number of trips they take is lower than pre-pandemic levels. For instance, the Multi-day Frequent cluster took 28.4 trips on average in January 2020 and 24.7 trips on average in October of the same year. The Multi-day Occasional Peak cluster is traveling less during the pandemic than before, with 11.6 average trips before the pandemic and 8.8 average trips during the pandemic. This is a drop of nearly a quarter. The reasons for this may be similar to the reasons for lower ridership among frequent, occasional, and peak clusters: “essential” workers might not be traveling five days a week as the traditional commuters were before the pandemic.

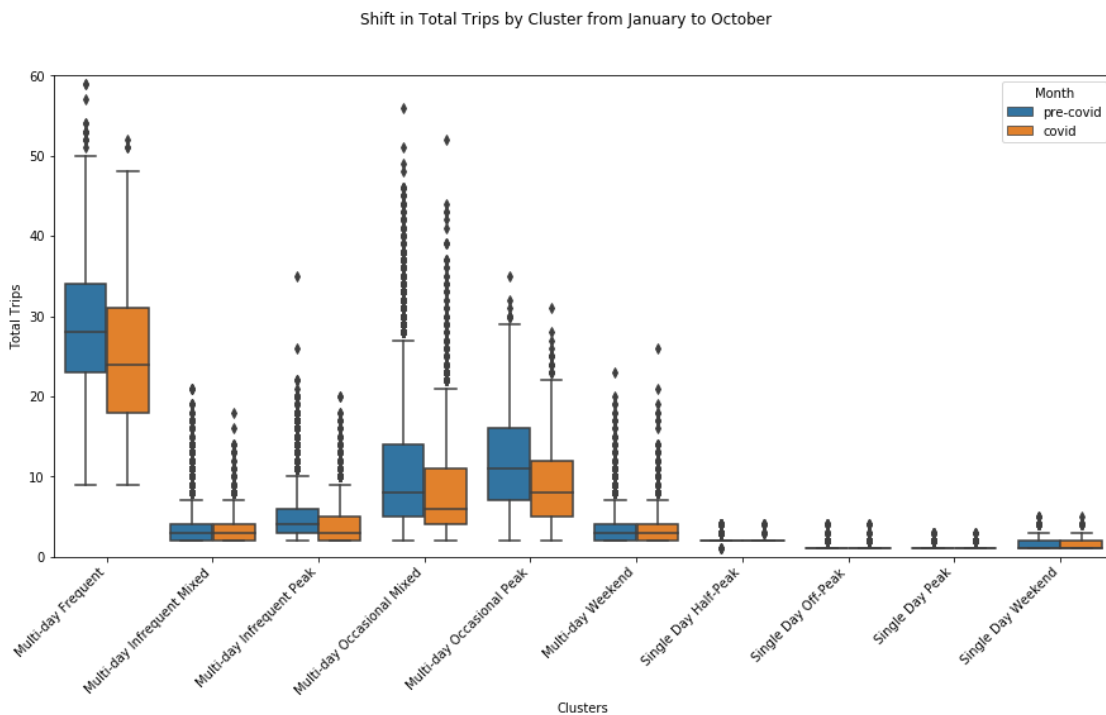


Figure 3-13: Total trips taken on average by each user by cluster in January 2020 (*pre-covid*) and October 2020 (*covid*)

Figure 3-14 shows the proportion of each cluster that is either new to mTicket in October 2020, new to mTicket since the beginning of the pandemic (in this case, starting April 1, 2020), or if they have used mTicket prior to the pandemic. Interestingly, over half of all users (57%) were new to mTicket in October 2020. However, the Frequent and Occasional clusters are more likely to have users who have both used mTicket before the pandemic and have also used mTicket since the beginning of the pandemic. It should be noted that just because a user is new to mTicket does not mean they are new to the commuter rail system. Many of these users may have been purchasing tickets through Fare Vending Machines (FVMs) or train conductors but have switched to purchasing tickets through mTicket, possibly for sanitary reasons (fewer physical interactions).

Nonetheless, this suggests that frequent and occasional users are more likely to have returning mTicket users than infrequent or weekend users.

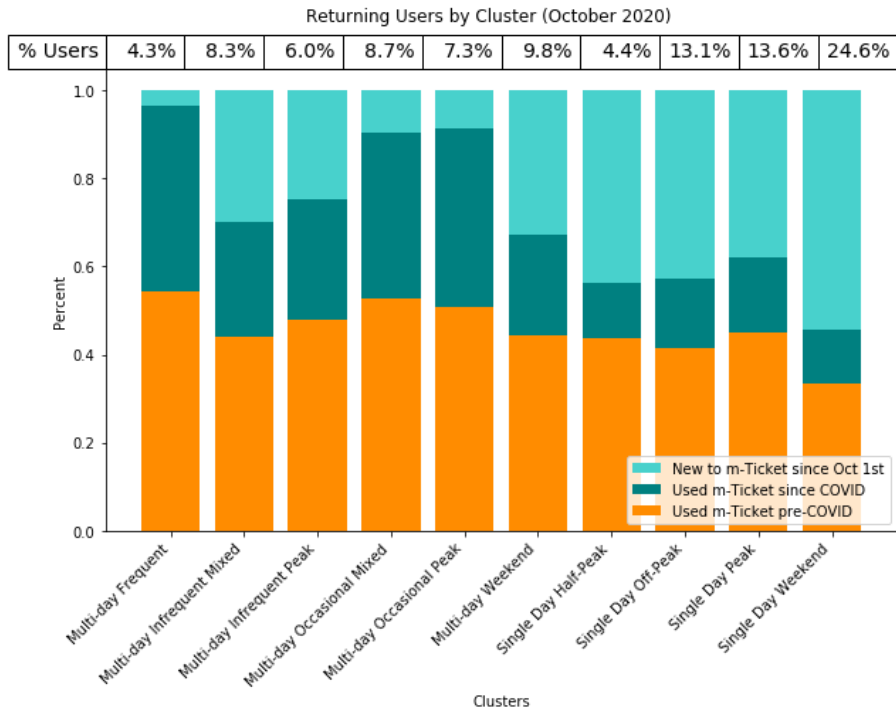


Figure 3-14: Proportion of each October 2020 cluster separated by prior mTicket use. One group used mTicket before the pandemic (before April 1, 2020), the other first used mTicket between April and October 2020, and the last just started using mTicket in October (mTicket only data).

In total, only 19.7% of mTicket users in October 2020 also used the mTicket system in January 2020. While that is a subset of an already small sample, there are nearly 5,700 unique accounts that used mTicket both in January 2020 and October 2020. Figure 3-15 shows the distribution of these users by their October segmentation. For example, for those who traveled on mTicket in both January and October of 2020, sixty percent of the October Multi-day Frequent cluster was also in the January Multi-day Frequent cluster. In fact, those who were previously Multi-day Frequent riders in January are most likely to be in a Peak cluster in October. Additionally, previously Multi-day users are more likely to be Peak users in October. Overall, this matches previous analyses showing similarities between frequent, occasional, and peak users.

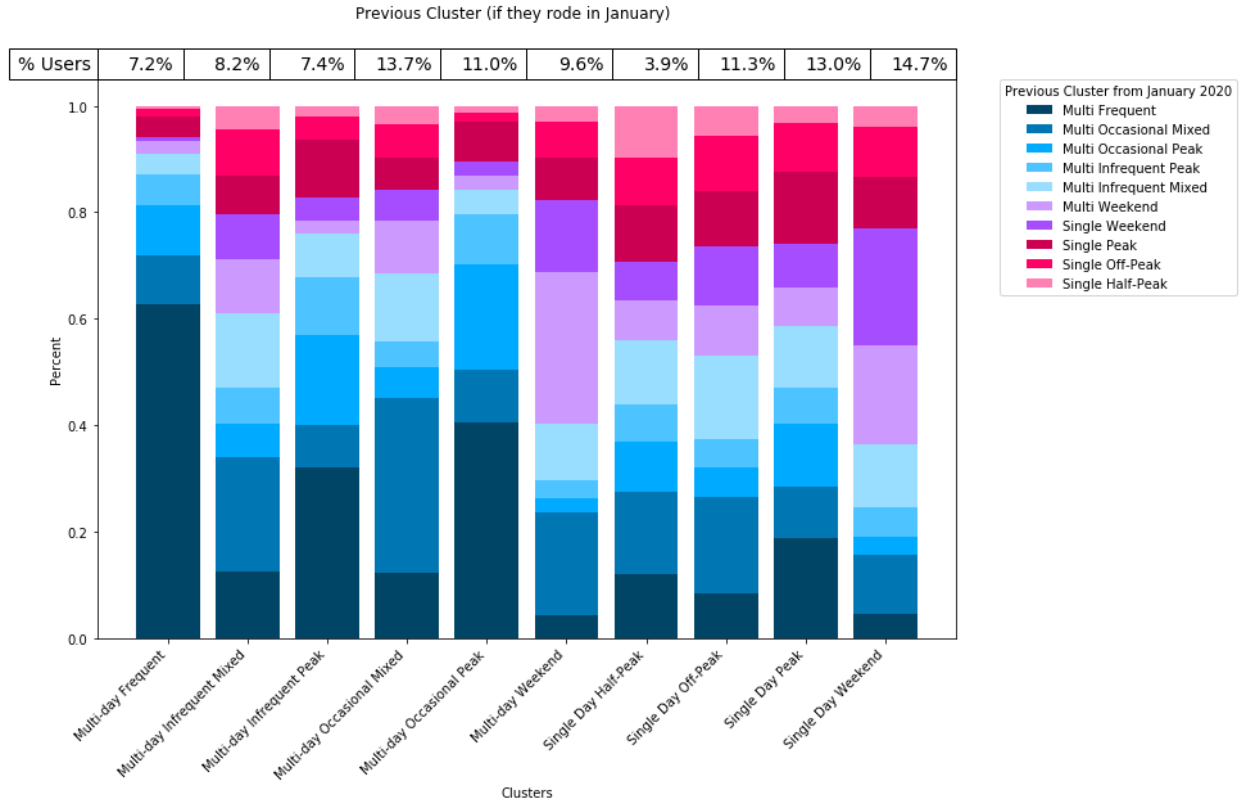


Figure 3-15: For October 2020 mTicket users who also traveled in January (19.7%), the figure shows the clusters they were previously segmented into. The horizontal categories are the clusters for October 2020 and the vertical bars represent January 2020 clusters.

The clustering analyses of January 2020 and October 2020 found that the commuter rail users who left the system were mostly frequent, occasional, and peak users, and the drastic decline in ridership is primarily attributed to the exodus of the Frequent cluster. This cluster is likely to be traditional commuters who switched to a work-from-home structure at the onset of the lockdown and spread of the pandemic in Massachusetts. With uncertainty on when the pandemic would subside and how often users might be traveling each month, monthly pass sales have drastically declined. Section 3.6 discusses a new fare product that was introduced during the pandemic to mitigate the uncertainty and lower ridership during the pandemic. Section 3.7 analyzes the user-types who purchased the new product and the success of targeting its intended audience and fulfilling its purpose.

3.6 A New Flexible Pass Option

The COVID-19 pandemic led to drastic declines in transit ridership and different travel patterns among those who continued to use transit. Section 3.4 and Section 3.5 explored some of the ridership declines during the pandemic and how travel patterns changed. In the first few months of the pandemic, it was known that ridership declined significantly and the future of commuting was uncertain. The uncertainty of when the pandemic would subside and how commuters were traveling led the MBTA to debut a new flexible pass option, in the hopes of catering to the needs of occasional and frequent commuters.

Before the pandemic, frequent users would often purchase monthly passes and occasional and infrequent users would purchase pay-as-you-go tickets. When the pandemic hit, people were uncertain how much they would travel. The likelihood of a rider knowing they would hit the pass

multiple (and “get their money’s worth”) decreased. To respond rapidly to this uncertainty in travel, the MBTA introduced the Flex Pass in July 2020. The hope was to offer a pass-like ticket for users who traveled often but not enough to break-even with the Monthly Pass. However, since it would take months to update all of the Fare Vending Machines to include the new product, the MBTA opted to sell the Flex Pass on mTicket only to quickly add it to circulation. The Flex Pass includes five one-day passes at a 10% discount of five Round Trip tickets. However, a Round Trip ticket has a 90-day expiration while the Flex Pass can only be used in a 30-day period.

The Flex Pass is designed to be between pay-as-you-go and a Monthly Pass. If a user travels twice per day on five distinct days in a 30-day span, they would spend 10% less than five Round Trip tickets. If they travel on fifteen days in a month, they would spend less on three Flex Passes than one Monthly Pass. However, frequent commuters would still benefit from a Monthly Pass if they travel more than 16 days, which is the pass multiple for most Monthly Passes on commuter rail (as the pass multiple varies slightly by zone). Thus, a Flex Pass is cost effective for people who travel between five and fifteen days per month, which are occasional and frequent users.

3.7 Analyzing the Flex Pass

While the Flex Pass debuted on July 1, 2020, fares were not validated on mTicket until around July 20, 2020 due to COVID-19 social distancing protocols in place in the early summer. Since its debut, the Flex Pass has captured around 6-7% of mTicket revenue. Figure 3-16 shows the share of each fare product on mTicket between August 2020 and January 2021. During the pandemic, One Way and Round Trip tickets have been the most popular products, likely because of the infrequent users and uncertainty on how often someone might be traveling on commuter rail. This section examines the users who purchase and use the Flex Pass and is divided into three subsections. The first (Subsection 3.7.1) explores the clusters and ridership behaviors of Flex Pass users compared to other fare product users. Subsection 3.7.2 looks at how people used their Flex Pass and its financial implications for users. Subsection 3.7.3 looks beyond the Flex Pass at all PAYG users who generally would have benefited from a Flex Pass but chose instead to purchase each ticket individually. Together, these three sections examine different aspects of the Flex Pass to better analyze its impact on commuter rail ridership.

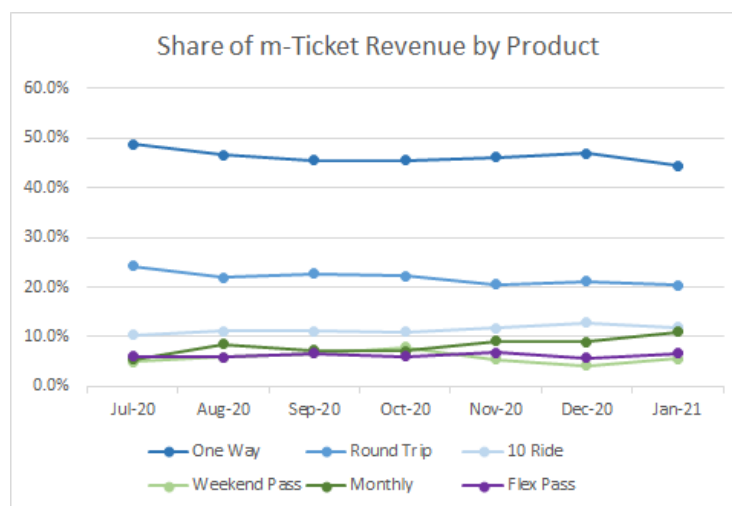


Figure 3-16: Share of revenue for each fare product on mTicket (not scaled)

3.7.1 Flex Pass Clusters

The Flex Pass was intended to be a pass option for commuters that were occasional or frequent riders. Examining the October 2020 clusters, the vast majority of Flex Pass purchasers were frequent, occasional, and peak users. In fact, 86.5% of users who primarily used Flex Pass in October were in the Multi-day Frequent, Multi-day Occasional (Peak and Mixed), or Multi-day Infrequent Peak. Over half (55%) of all primary Flex Pass users were in the Multi-day Frequent or Occasional Peak clusters. Looking at users who explicitly rode in both January and October 2020, only 2.2% of those users adopted a Flex Pass. However, those who, in January, were Multi-day Frequent (5.9%) and Occasional Peak (2.8%) users were more likely to purchase a Flex Pass in October 2020. This suggests that the pass was preferred by frequent, occasional, and peak users, as was intended.

For all but three clusters, over 80% of users primarily used pay-as-you-go (PAYG) tickets (see Table 3-4). Two of those three clusters are the Weekend clusters, which had between 53% and 59% of the users primarily purchase a Weekend Pass. The other cluster is the Multi-day Frequent cluster, which has the highest proportion of users purchasing a Monthly Pass (56%), whereas in January 2020 roughly 75% of the Multi-day Frequent cluster purchased a Monthly Pass. The Flex Pass was most common among the Frequent, Peak, and Occasional clusters. Outside of the Multi-day Frequent cluster, the Flex Pass had a higher share of all trips than users in the other clusters. This suggests that within each cluster, Flex Pass users take more trips than their PAYG or Weekend Pass counterparts. Interestingly, the Flex Pass had a higher user share of the Peak clusters (Occasional and Infrequent) than Monthly Pass holders, but not within the Occasional Mixed cluster. This suggests that peak users, who were the most likely to leave the system during the pandemic, are more drawn to the Flex Pass than a Monthly Pass (with the exception of Frequent users).

Table 3-4: Percent of users and trips in October 2020 within each cluster by the product they purchased (scaled to estimate all commuter rail users)

Cluster	PAYG		Flex Pass		Monthly Pass		Weekend Pass	
	Users	Trips	Users	Trips	Users	Trips	Users	Trips
Multi-day Frequent	39.3%	30.9%	4.7%	4.5%	56.0%	64.6%	0.0%	0.0%
Multi-day Occasional Peak	88.7%	82.5%	5.7%	8.2%	5.6%	9.4%	0.0%	0.0%
Multi-day Occasional Mixed	81.7%	67.6%	2.3%	3.9%	9.2%	24.6%	6.8%	3.9%
Multi-day Infrequent Peak	93.7%	89.9%	3.8%	6.2%	2.4%	3.9%	0.0%	0.0%
Multi-day Infrequent Mixed	91.5%	91.0%	1.0%	2.1%	0.9%	2.0%	6.6%	4.9%
Multi-day Weekend	41.0%	37.1%	0.0%	0.0%	0.0%	0.0%	59.0%	62.9%
Single-day Peak	99.5%	99.4%	0.4%	0.5%	0.0%	0.0%	0.0%	0.0%
Single-day Half-Peak	99.4%	99.4%	0.5%	0.5%	0.0%	0.0%	0.0%	0.0%
Single-day Off-Peak	99.8%	99.8%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
Single-day Weekend	47.5%	45.3%	0.0%	0.0%	0.0%	0.0%	52.5%	54.7%

Flex Pass users are primarily frequent, occasional, and peak users, which would suggest that many of them had used mTicket prior to the pandemic (see Figure 3-14). However, since the Flex Pass is only offered on mTicket, many users who previously took commuter rail may have downloaded the mTicket app for the sole purpose of purchasing a Flex Pass. In October 2020, roughly 47% of Flex

Pass users had used mTicket prior to the pandemic (before March 2020), which is slightly higher than the 43% of all mTicket users in October who had used mTicket prior to the pandemic. Even more intriguing is that only 14% of Flex Pass purchasers used mTicket for the first time in October 2020, whereas that number was 35% for all users in that month. This suggests that Flex Pass purchasers are likely to be more familiar with the app than the general population. Given the novelty of the product and the exclusivity to one fare channel, the Flex Pass might not be known or familiar to many commuter rail riders. Add on top of that the difficulty of marketing the product in the middle of a global pandemic and it is possible that not many commuter rail riders were aware of the product.

What were Flex Pass users purchasing before the pandemic? A quarter of users who purchased at least one Flex Pass during the pandemic had purchased a Monthly Pass in January 2020. Over 70% had purchase a pay-as-you-go ticket in January 2020. This suggests that the Flex Pass might be attracting pay-as-you-go users who have frequent, occasional, or peak travel behaviors. In fact, since the introduction of the Flex Pass, more people have been switching between purchasing a Flex Pass and pay-as-you-go ticket. Figure 3-17 shows the most commonly purchased product for people who have purchased at least one Flex Pass since it debuted. All pay-as-you-go tickets were combined into one category, as they tend to have similar travel behaviors. Each user is lightly shaded so that only consistent trends appear in the figure. They are also colored by what their preferred purchase was before the pandemic (red for Monthly Passes and blue for pay-as-you-go tickets). Since the Flex Pass was introduced, a lot of the early adopters were previously pay-as-you-go users, although many previously Monthly Pass users were also purchasing Flex Passes. However, while the hope was for frequent users to use the Flex Pass until their ridership increased and eventually switch to a Monthly Pass, it appears a larger portion of Flex Pass users reverted back to pay-as-you-go tickets after trying the Flex Pass. In fact, 54% of people who purchased a Flex Pass never bought a second. However, if a person primarily purchased Flex Passes in a given month, there is a 44% chance they stick with the Flex Pass in the subsequent month. This suggests that Flex Pass users are either sticking with the Flex Pass or switching to pay-as-you-go, with few shifting to Monthly Passes.

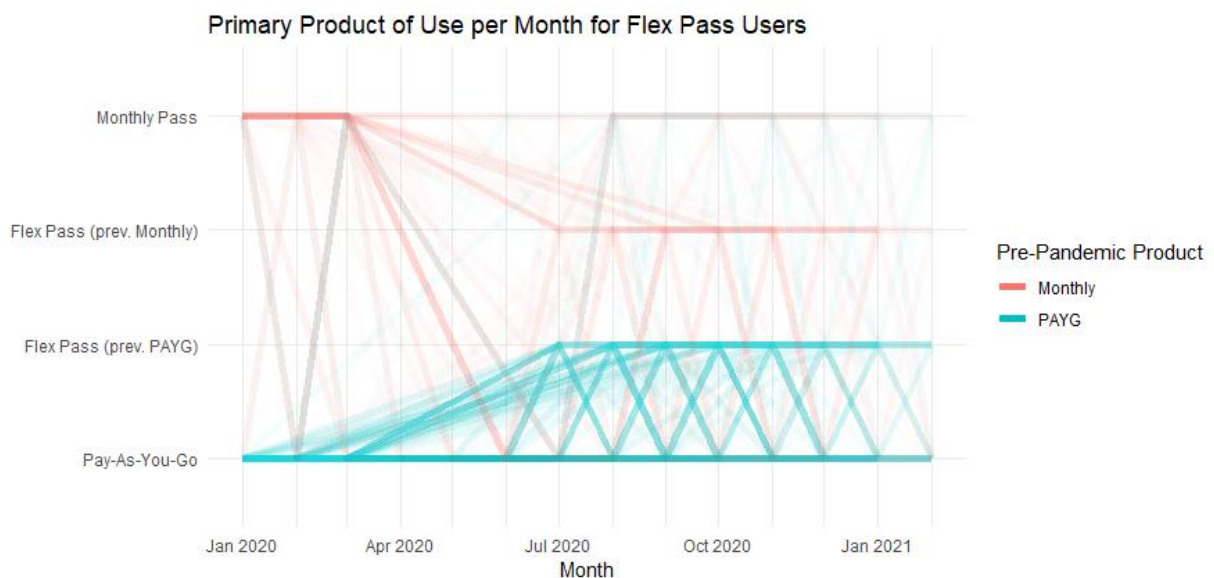


Figure 3-17: Most used product per month by Flex Pass users (mTicket only)

How do Flex Pass users compare to everyone else? Using the October 2020 clusters, Figure 3-18 shows how users who primarily used the Flex Pass often took more trips than the other users. This is especially noticeable within the Multi-day clusters, except the Multi-day Weekend cluster, which did not have any user primarily purchase a Flex Pass. The mixed clusters (Multi-day Occasional Mixed and Infrequent Mixed) who primarily purchased a Flex Pass had over double the average number of trips as the non-Flex Pass counterparts. Even the occasional clusters had between 50-70% higher average trips among Flex Pass users. Whether the more frequent traveling users self-select the Flex Pass to match their travel patterns or whether they take advantage of the unlimited commuter rail access each day and ride more often to use all five days is unclear.

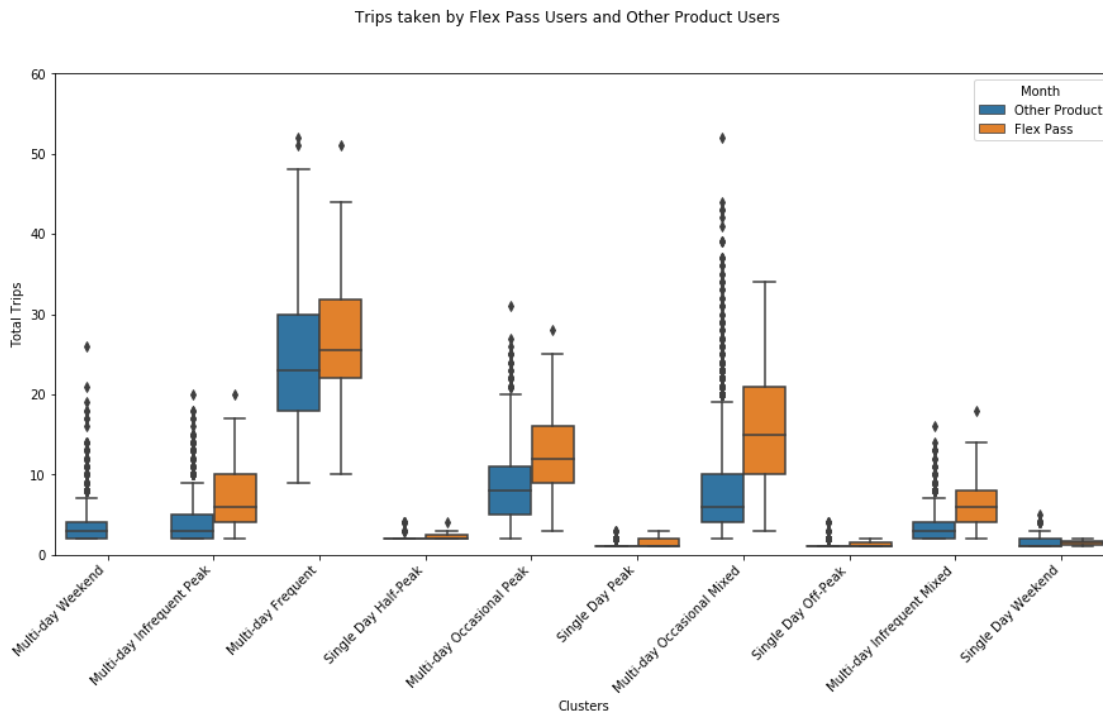


Figure 3-18: Distribution of total trips taken per cluster, separated by if they primarily used a Flex Pass in October 2020 (mTicket only)

Overall, the Flex Pass is mostly being used by frequent, occasional, and peak commuter rail users. However, they are also users who frequent the pay-as-you-go tickets and have fluctuated between the pay-as-you-go tickets and Flex Pass since the debut of the new product. Flex Pass users are more likely to have used mTicket in the past as well, suggesting they are either exposed to the ticket through the app or the ticket appeals more to returning mTicket users. The new pass also appears to attract the higher ridership users in each cluster – or possibly encourages them to travel more often. Overall, the Flex Pass is being purchased by targeting its intended audience and, based on accounts from the MBTA, is popular among its users, even if it only captures between 6-7% of all mTicket sales.

3.7.2 Usage of the Flex Pass

While the Flex Pass offers a discounted rate on commuter rail compared to round trip tickets, the 30-day expiration can leave tickets unused. Each Flex Pass consists of five one day passes. Of the one day passes that have expired by the end of January 2021, 13% went unused. Note that these

unused passes are only a portion of most Flex Pass products that have one or more expired on day passes. For example, someone might have purchased a Flex Pass and used four of the five one day passes before the 30-day expiration but was unable to travel a fifth day and left that pass unused. This suggests that there are users who don't get the full value out of their Flex Pass. In fact, over a third of all Flex Pass purchases averaged less than 2 trips per One Day Pass. Thus, it is likely that many Flex Pass users did not get their full value's worth of the pass. However, many Flex Pass users also rode more than twice in one day, as shown in Figure 3-19. Therefore, some users likely had a higher use value than the price of the Flex Pass, while others had a use value below Flex Pass price.

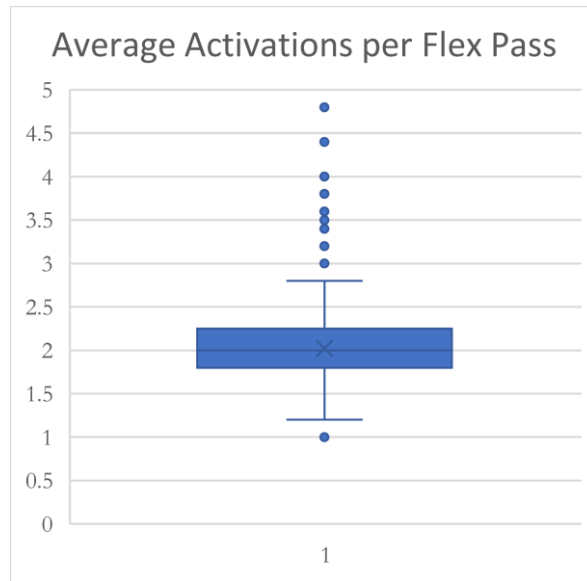


Figure 3-19: Average activations per Flex Pass product (averaged across all five One Day Passes)

To better understand how many users benefited from the Flex Pass, the “use value” for each Flex Pass was calculated and compared to the counterfactual of purchasing five round trip tickets for the same zone. The “use value” is the amount a pass product would be worth had every trip been paid on a PAYG ticket. Since a Flex Pass offers a 10% discount compared to five round trip tickets, using each Flex Pass ticket at least twice would be financially beneficial. Figure 3-20 shows the number of Flex Passes by the number of trips validated on each pass. Values with 9 trips or more indicate that the rider used the Flex Pass for at least the cost of the pass. Values of 8 trips or fewer indicate that the rider had a lower use value than the cost of the pass. In total, 64% of Flex Pass buyers broke even or better with the Flex Pass. Summing the difference between the use value and the PAYG equivalent produces a \$45,200 surplus from the purchases that had a positive use value and a \$43,500 loss from the purchases that did not break even. If users purchased PAYG tickets equivalent to the number of trips they took on Flex Pass, they would have spent, in aggregate, an additional \$1,700 ($\$45,200 - \$43,500 = \$1,700$) on tickets, or an average of \$0.44 per Flex Pass sold. However, passes provide a zero marginal cost benefit, meaning each additional trip on commuter rail is effectively free after taking the first trip on a One Day Pass.

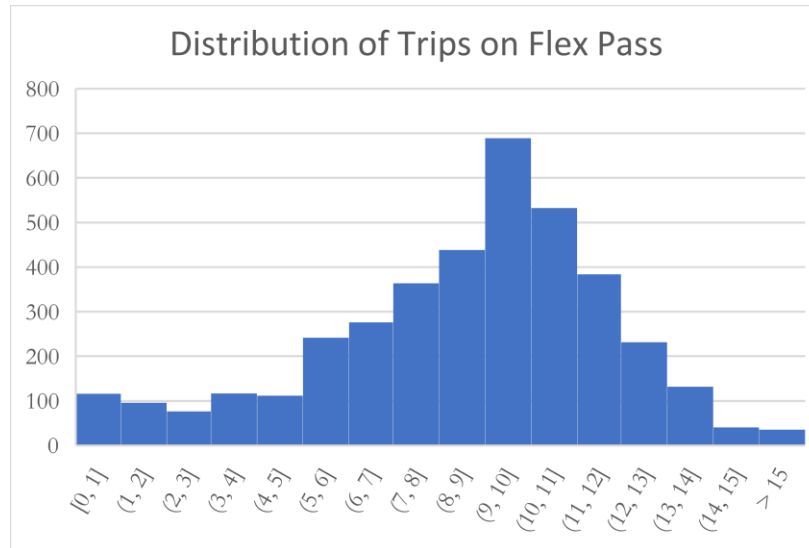


Figure 3-20: Distribution of trips on Flex Pass. Trips greater than or equal to 9 indicate that the user "got their money's worth" with the Flex Pass.

3.7.3 Who Else Could Benefit from a Flex Pass?

Another way to try and understand the impact of the Flex Pass is to analyze who could have benefited from a Flex Pass but never purchased one. These are the users who should be targeted in any future marketing campaigns (see Section 4.5 for more on this topic). With other passes on mTicket, determining the benefit of a pass is easy since the active period of the pass is calendar-based. For example, PAYG users who would have benefited from a Monthly Pass are those who spend more money on PAYG passes than a Monthly Pass over a given month. The calculation for Flex Passes is not as simple since the Flex Pass is available for 30 days after its original purchase. Therefore, a rolling window method is used to estimate the number of trips taken and unique days on commuter rail over a 30-day period. Due to the ease of purchasing a Flex Pass whenever and wherever since it is a mobile app, this analysis assumes the user would have purchased the Flex Pass before their first activation.

The rolling window method was applied to all mTicket PAYG tickets between September 2020 and February 2021. This begins shortly after the Flex Pass was first introduced and ends with the most updated data available. Each day a user takes commuter rail on mTicket a summation of the trips and number of unique days traveled for the next 30 days is calculated. This is used to consider the counterfactual of having used an mTicket Flex Pass. Over the period of analysis, 6.6% (5725 riders) of all users who used PAYG tickets would have at least broken even on a Flex Pass at least once. Breaking even on a Flex Pass is equivalent to taking nine trips on PAYG within 5 unique days of travel.

However, the percent of users who would have benefited from a Flex Pass varies by the most common type of fare product purchased. This difference is shown in Table 3-5, which shows the number and percent of the users who would have benefited from a Flex Pass grouped by the fare product they purchased most often. As can be seen, over half of all 10 Ride users would have benefited from a Flex Pass at least once over the analysis period. Almost 10% of users who primarily purchase Round Trip tickets would have benefited from a Flex Pass as well. This follows the previous analysis that 10 Ride users are most similar to Flex Pass and Monthly Pass users in regards to their travel patterns.

Table 3-5: Percent and count of users who would have benefited from purchasing a Flex Pass ("Flex Pass Benefit")

	Flex Pass Benefit	All Users	Percent
One Way	2339	62769	3.7%
Round Trip	2116	21776	9.7%
10 Ride	1270	2339	54.3%
Total	5725	86884	6.6%

The rolling window method calculates the 30-day moving window for each day a user took commuter rail with mTicket. Another way of determining the potential Flex Pass users is to calculate the percent of user-days in which a Flex Pass would have been cheaper (or the same price). For example, if a person travels for six days over a 30-day span and makes a round trip on each of those days, then there are two instances in which the person could have purchased a Flex Pass for a 10% discount (on the first and second day of use during the 30-day period). This would be calculated as two user-days. Over the analysis period, 11.8% of the user-days would have been cheaper (or the same price) had they been a Flex Pass. Table 3-6 breaks this value down by the most common fare product purchased by each user. Of all days a 10 Ride mTicket user took commuter rail, 30% of them would have been financially beneficial had they used a Flex Pass instead. This value is 17% for Round Trip users and 6% for One Way users. All of these are higher than the percent of unique users who had at least one user-day with a financial benefit, suggesting that the same users have multiple days in which they would have benefited from a Flex Pass.

Table 3-6: Percent and count of user-days that would have been cheaper or just as expensive had the user purchased a Flex Pass ("Flex Pass Benefit")

	Flex Pass Benefit	All User-Days	Percent
One Way	17244	278425	6.2%
Round Trip	16367	93859	17.4%
10 Ride	17337	57991	29.9%
Total	50948	430275	11.8%

So why aren't these users purchasing the Flex Pass? There are many potential reasons why these PAYG users are opting for the PAYG tickets rather than a Flex Pass. One reason, which will be discussed further in Chapter 4, might be because these users are unaware of the Flex Pass. Given that the pass was quickly created during the pandemic and was advertised while ridership was at low levels, it is possible that not many users were aware of the Flex Pass. Another possibility is that users were uncertain of how often they would travel in the next 30 days, making them hesitant to purchase a Flex Pass. All PAYG tickets have a 90-day expiration, which is likely more appealing to people who might not know how often they will travel in the short-term. For the 10 Ride users, it is possible the times they would have benefited from a Flex Pass were when they still had 10 Ride tickets left. Nonetheless, the attractiveness of the Flex Pass did not appear to be great enough to convince many PAYG users to switch. Section 3.8 suggests alternative product designs that might be more appealing to users while still functioning as a half-step between PAYG tickets and a Monthly Pass.

3.8 Alternate Product Design Ideas and Future Implementations

As many companies return to the office, it is likely that some jobs will result in workers commuting less than five days a week to the office. If this is the case, then the MBTA would need to reconsider the pass multiple on the Monthly Pass or develop a new pass that can capture the ridership from these riders that do not meet the current pass multiple but still consistently take commuter rail. This section proposes alternate Flex Pass structures that serve a similar purpose and target audience but with greater benefits.

Before suggesting a new pass product, it is helpful to understand what the current market looks like in regards to fare products. Figure 3-21 shows the proportion of fare products used by all commuter rail users categorized by the number of days they traveled in January 2020 (before the pandemic). The figure accounts for all commuter rail users by assuming a similar use distribution for non-mTicket users and proportionally scaling by primary fare product used. There is a clear decline in the proportion of users who purchase One Way and Round Trip tickets as the number of days traveled increases. This follows expectations as One Way and Round Trip tickets are designed for users who travel infrequently. Monthly passes are most common among users who travel 16 or more days in a month (just over three work weeks). Finally, users who purchase 10 Ride tickets primarily tend to travel between 6 and 15 days per month. While the product shares for each range are as expected, there are still users who still purchase a Monthly Pass despite traveling less than 10 days in a month and users who purchase PAYG tickets while traveling more than 20 days in a month. This “irrational” decision-making is expected in consumer behavior, as users are not perfectly rational or deterministic.

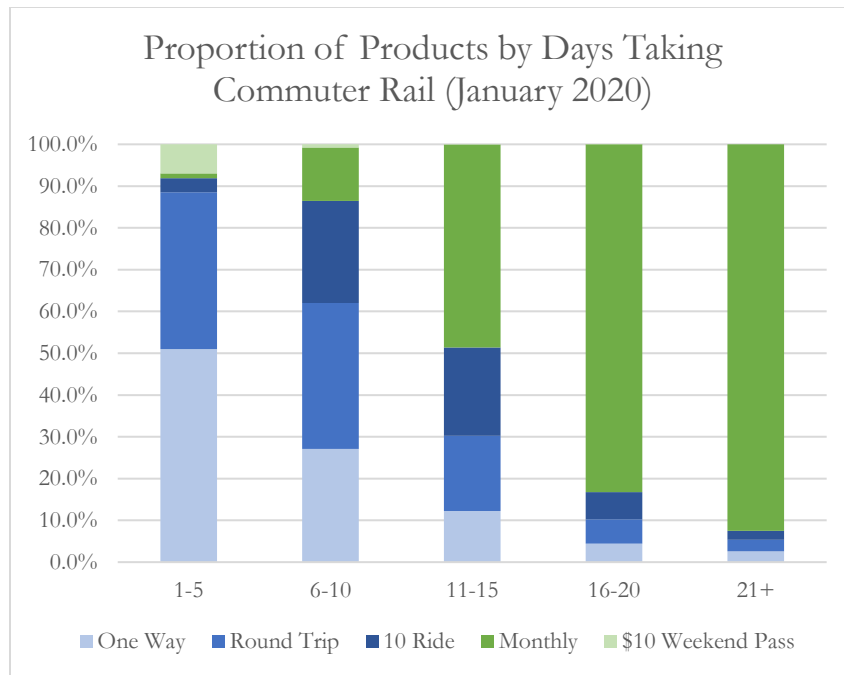


Figure 3-21: Proportion of users by number of days in a month they traveled based on the fare product they primarily used in January 2020 (scaled to estimate entire commuter rail system)

Figure 3-22 shows the same graph as Figure 3-21, except using October 2020 data (during the pandemic). It should be noted that ridership was significantly lower during the pandemic, so each of these proportions represent many fewer users than in January. Unlike the pre-pandemic users,

October had a smaller Monthly Pass share among users who traveled more than 20 days compared to those who traveled between 16 and 20 days. This could be in part due to the uncertainty in travel that riders faced throughout the pandemic. Many commuter rail passengers might have preferred purchasing PAYG tickets since they were uncertain how much they would travel. Despite low shares, the Flex Pass was most popular with users who traveled between 6 and 15 days in October. A few Flex Pass users also traveled more than 20 days, although this was still a relatively small amount. The target ridership group are users who travel between 6 and 15 days per month.

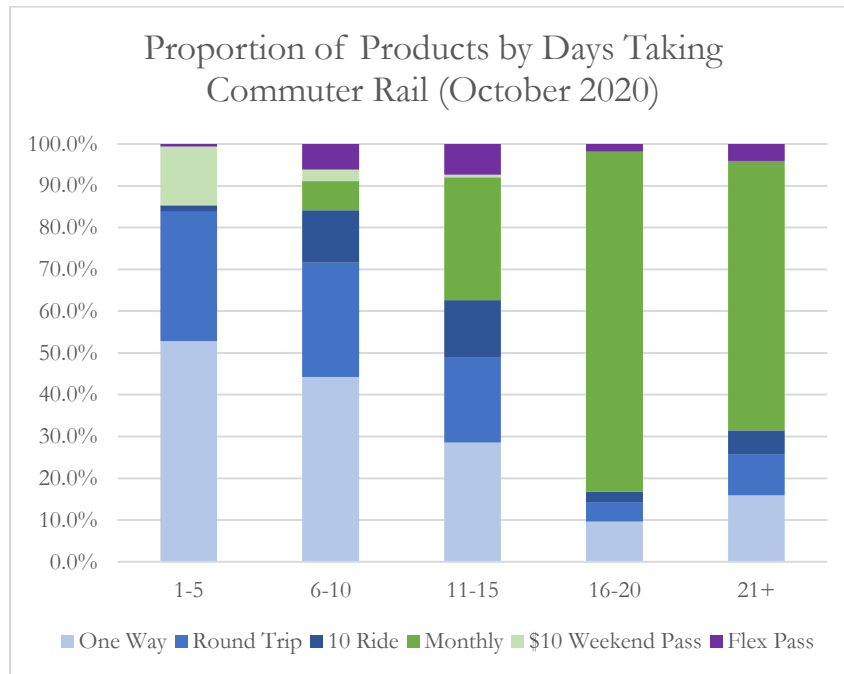


Figure 3-22: Proportion of users by number of days in a month they traveled based on the fare product they primarily used in October 2020 (scaled to estimate entire commuter rail system)

There are many alternative fare product structures that could be explored in this analysis. This analysis will focus on two product designs, one of which is similar to the Flex Pass and another that offers a given number of trips over a length of time. The product designs are compared against varying discount levels and expiration lengths. Each product examines a 10%, 15%, and 20% discount and considers an expiration limit of 30, 45, or 60 days. The Flex Pass, for example, offers five one-day passes at a 10% discount with a 30-day expiration period. This could be redesigned also as 10 one-day passes and offered at a 10%, 15%, or 20% discount. Additionally, the 30-day expiration period could be extended to 45 days to offer additional flexibility.

3.8.1 Alternate Product Design Methodology

There are two primary desired outcomes for this analysis. The first is to compare the attractiveness and adoption rate of various product designs. The second is to estimate post-pandemic monthly ridership for each product. Reaching these outcomes requires estimating ridership after the pandemic, especially for the second outcome. While there are still many unknowns in regards to ridership post-pandemic, the assumption at the MBTA and other transit agencies has been that ridership will be below pre-pandemic levels for the next few years. In the most optimistic scenario, the MBTA estimated fare revenue for Fiscal Year 2026 to be only 89% of what it was in FY 2019 (O'Hara & Panagore, 2021). Therefore, the assumptions of post-pandemic ridership growth for this

analysis lie somewhere between current ridership during the pandemic and ridership from before COVID-19.

To estimate post-pandemic ridership, there must be information on pre-pandemic and during the pandemic ridership levels, to determine the upper and lower limits, respectively. This analysis uses two time periods for analysis; the first is from July 2019 to February 2020 and is used to estimate pre-pandemic ridership and the second is from July 2020 to February 2021 to estimate ridership during the pandemic. The eight-month range was used to minimize seasonal variations while also capturing enough data points for the analysis during the pandemic, since ridership levels were much lower. Additionally, the alternative product designs have an expiration period of 30 to 60 days on a rolling window, depending on the design. Therefore, having the analysis span eight months ensures fully covering potential users.

One method of determining the potential benefit of a new product is through a rolling window method, which calculates user-days that a person would have benefitted from purchasing a specific product. A “user-day” represents a unique user (or account, in this instance) on a unique day. For this analysis, user-days are only calculated on days that a rider took commuter rail. If, for example, user A rode commuter rail on 10 different days and user B rode on 5 different days, then the total number of user-days would be 15 between the two of them. Each user-day is then categorized as being a “beneficial” or “non-beneficial” for each pass. A “beneficial” user-day is one in which the subsequent trips taken on that user-day (including the current user-day) would have been cheaper or the same cost if purchased on one of the alternative fare products. “Non-beneficial” user-days are those in which it would have been cheaper not to purchase an alternative fare product.

Take, for example, *Table 3-7* as an example of a commuter rail passenger. The days this user traveled are marked with a number (indicating a “user-day”) while the days they did not travel are marked with a red “X.” Under the existing Flex Pass, a rider can have unlimited travel on any five days within a 30-day period at a 10% discount of purchasing five Round Trip tickets (i.e. one free trip). The cells in green show a “beneficial” user-day, which means that the user would have benefitted from purchasing a Flex Pass because they rode at least 9 times in the next five days. For example, this user rode twice in each of the first five days they traveled, so if they had purchased a Flex Pass in the first day then they would have saved 10% on those five days of travel. The cells in yellow signal a “non-beneficial” user-day, where the user would have saved money purchasing individual pay-as-you-go tickets. Note that each day (or cell, in this case) is highlighted green only if the subsequent five days add up to 9 or more trips.

Table 3-7: An example month of a user. X's on days indicate no trips were taken. A number indicates the amount of trips taken that day. Green cells are "beneficial" user-days and yellow are "non-beneficial" user-days based on the current Flex Pass.

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Week 1	X	X	2	2	X	X	X
Week 2	2	X	2	X	2	X	X
Week 3	1	2	X	X	X	X	X
Week 4	X	X	1	2	X	X	X
Week 5	X	2	X	2	2	X	X

The beneficial and non-beneficial user-days are calculated for both analysis periods (before and during the pandemic). Due to low ridership and travel restrictions, the beneficial user-days were much lower during the pandemic than they were before the pandemic. Since ridership is expected to

be somewhere between current ridership during the pandemic and no higher than pre-pandemic ridership, four scenarios are analyzed that estimate a low, moderate, high, and full return of ridership. Each scenario is applied to each pay-as-you-go fare product to account for the slight differences in travel behaviors. For example, there are only about 17% of total user-days during the pandemic as there were pre-pandemic for One Way tickets. However, 10 Ride tickets are down to around 5% of pre-pandemic user-days. This reflects the trends of 10 Ride users more likely to be frequent, peak users than One Way and Round Trip users.

The first scenario (Scenario 1) assumes a low ridership return of only one third of the difference between current and pre-pandemic ridership returns. Scenario 2 assumes a moderate return that splits the difference between during and pre-pandemic user-days. The optimistic scenario (Scenario 3) assumes two-thirds of the difference between during and pre-pandemic ridership returns. Scenario 4 assumes a full return of ridership to the system and uses pre-pandemic ridership levels. Commuter rail has the lowest remaining ridership throughout the COVID-19 pandemic compared to a year prior, so a return to the system is expected to be slow and behind other modes. *Table 3-8* shows the ridership estimates for each scenario in comparison to the ridership in January 2020 (pre-pandemic) and October 2020 (during the pandemic). Note that the Flex Pass was not offered until July 2020. Additionally, the scenarios estimate the Flex Pass ridership assuming no changes to the fare product design.

Table 3-8: Ridership estimates per month by fare product for each scenario

	January 2020	October 2020	Scenario 1	Scenario 2	Scenario 3	Scenario 4
One Way	332,679	66,211	126,844	165,068	203,293	279,742
Round Trip	437,312	51,256	139,047	190,784	242,520	345,994
10 Ride	275,535	13,257	80,925	115,841	150,757	220,589
Monthly Pass	1,755,992	66,704	617,436	896,633	1,175,830	1,819,508
Flex Pass	-	9,909	44,940	63,065	83,950	117,442
Total	2,801,517	207,337	1,009,191	1,431,391	1,856,350	2,783,275

While the beneficial user-days and scenarios help show the potential gain from each alternative fare product, it does not inform the likelihood of purchasing the fare product. The “adoption rate”, or the percent of beneficial and non-beneficial user-days that were paid for by an alternate fare product, is estimated partially based on the current Flex Pass use profiles. The Flex Pass had an adoption rate of 21.8% for all beneficial user-days and 4.5% for all non-beneficial user-days. That means that only about one out of every five days in which a user would have benefitted from a Flex Pass actually was paid for using a Flex Pass. Note that the non-beneficial user-days does not necessarily mean the user did not benefit from a Flex Pass, as it could have been one they purchased prior to that day. For instance, if the example user from Table 3-7 purchased a Flex Pass on Wednesday of Week 1, they would have used a Flex Pass to pay for three beneficial user-days (Wednesday and Thursday of Week 1 and Monday of Week 2) and two non-beneficial user-days (Wednesday and Friday of Week 2).

The low adoption rate on beneficial user-days could be due to many factors. One explanation is the low discount. While a 10% discount saves one trip, it might not be enticing enough for a user to purchase a Flex Pass that expires sooner than PAYG tickets (30 rather than 90 days). Offering a higher discount would likely increase the adoption rate of the Flex Pass as it offers more flexibility for commuter rail passengers to take advantage of the full value of the pass. Another potential reason for low adoption rates for the Flex Pass is because it provides Day Passes rather than trips.

Many commuter rail users only take one trip per day, rather than a round trip. There are many potential reasons for this but the most common is likely from carpooling with family members or others in one direction. For example, carpooling might be common in the morning when everyone gets in to work at the same time; but if someone stays late or leaves work early then they might commuter rail back. This analysis assumes an increase in the adoption rate for higher discounts and for the trip-based products (see Subsection 3.8.3 for example trip-based products). For every 5% increase in the product discount, the adoption rate is assumed to add 10 percentage points. Additionally, trip-based products are assumed to add 10 percentage points to the adoption rate, as those are likely to be more attractive to users. *Table 3-9* shows the adoption rates for each of the discount levels and fare product types.

Table 3-9: Adoption rate for each discount and fare product type

Discount	10%	15%	20%
Flex Pass	21.8%	31.8%	41.8%
Trip-based	31.8%	41.8%	51.8%

Finally, based on the user-days, adoption rate (with the higher number assigned to the highest discount rate of 20%), and ridership return scenarios, a total estimate for number of monthly trips is made for each alternative fare product and scenario. *Table 3-10* shows the estimated trips per day and scaling factors used to estimate overall commuter rail ridership for each scenario. Average monthly trips are calculated from the actual average trips per day from before the pandemic and during the pandemic. Average daily ridership declined during the pandemic for each pass type so the estimated trips per day are determined by the mean from before and during the pandemic. For the alternate fare products, only Flex Pass data is available. However, ridership is expected to be somewhere between frequent pay-as-you-go products and the Monthly Pass. Thus, the pre-pandemic average daily trips were determined to be halfway between the 10 Ride and Monthly Pass average daily trips. The scaling values are the same as described in Section 3.3 with the alternate pass scaling being the PAYG average for scaling purposes. The PAYG average was used since the current Flex Pass is only available on mTicket. While it would be ideal that the alternate pass products be offered across the entire commuter rail system, that would not be possible to implement until the summer of 2022 at the earliest. Therefore, the scaling factor matches PAYG fare revenue on commuter rail, of which 70% is derived from mTicket.

Table 3-10: Trips per day and scaling factors by fare product

	One Way	Round Trip	10 Ride	Monthly Pass	Alternate Pass
Estimated Trips per Day	1.28	1.62	1.62	1.78	1.73
Scaling	1.21	2.07	1.08	7.50	1.44

3.8.2 Flex Pass Redesign

The Flex Pass at its current design offers five one-day passes at 10% discount that is available for 30 days. There are 6.6% of PAYG users and 11.8% of user-days that would have benefited financially from a Flex Pass under the current design (see Table 3-5 and Table 3-6). How many more people would have a financial benefit if the discount was 15% or 20%? What if the pass expired after 45 days rather than 30 days? What if the Flex Pass offered ten day passes rather than five? This subsection analyzes the potential catchment of PAYG users based on alternate Flex Pass designs.

The three different levers that can be altered on the Flex Pass are the number of day passes offered, the discount amount, and the expiration length. Table 3-11 shows the percent of user-days that would benefit from a Flex Pass broken down by the three pay-as-you-go products. The table also shows the user-days before and during the COVID-19 pandemic to show how ridership behaviors have shifted. The number of day-passes available is compared between 5 and 10, where the current Flex Pass offers 5 day passes. The discount changes between 10%, 15%, and 20%. The 5 day passes version is analyzed for a 10% (current) and 20% discount since a 15% discount would break even at 8.5 trips, which is marginally better than a 10% discount which breaks even at 9 trips. The 10 day passes version is analyzed with a 15% and 20% discount. A 10% discount is ignored as it is equivalent to purchasing two current Flex Passes, except for more day passes and a shorter expiration period (30 days in total rather than two 30-day periods consecutively). Finally, each alternative design is compared to a 30-day expiration period and a 45-day expiration period.

Note that a 20% discount of the Flex Pass would make the product comparable to the price of a Monthly Pass. To adjust for this, it is suggested that the Monthly Pass increase its discount to 30% (currently it is between 20% and 25%). Ridership on the MBTA is expected to be below pre-pandemic levels at least until 2026 so a top priority for the agency should be to get users onto transit as early as possible. This could be by offering deeper discounts on passes to encourage commuter rail travel over other transportation modes. Additionally, with the likelihood of reduced commuting due to an increase in work-from-home, the pass multiple for monthly passes are likely to be less attractive. A deeper discount will capture more riders who can work-from-home a few days per month. The Flex Pass redesign will then capture the occasional riders that would benefit from a discounted pass but do not travel enough to reach the pass multiple for a Monthly Pass.

As shown in Table 3-11, the percent of user-days that would benefit financially from a Flex Pass redesign increases as the discount rate and expiration period increase. The user-days were also considerably higher before the pandemic than during, which matches the reduced frequency of trips during the pandemic. Despite offering a higher discount, the 10 day-passes alternative design has less or nearly the same user-days than the existing Flex Pass, both during and before the pandemic. Increasing the discount on the Flex Pass from 10% to 20% would increase the user-days by around 50% during the pandemic and increase user-days by around 25% using pre-pandemic data. A deep discount of 20% on a Flex Pass would make the product comparable in price to the Monthly Pass. To adjust for this, it is suggested that the Monthly Pass increase its discount to 30% (currently it is between 20% and 25%). Ridership on the MBTA is expected to be below pre-pandemic levels at least until 2026 so a top priority for the agency should be to get users onto transit as early as possible. This could be by offering deeper discounts on passes to encourage commuter rail travel over other transportation modes.

Table 3-11: Percent of beneficial user-days before and during COVID-19 – or the user-days that would benefit from the various Flex Pass redesigns for pay-as-you-go users

Days		5				10			
Discount		10%		20%		15%		20%	
Expiration		30	45	30	45	30	45	30	45
One Way	During COVID-19	6.3%	6.7%	11.4%	12.1%	4.2%	5.1%	6.0%	7.1%
	Pre-COVID-19	15.4%	16.1%	23.4%	24.2%	12.0%	13.9%	15.3%	17.5%
Round Trip	During COVID-19	18.0%	19.6%	27.2%	29.3%	10.8%	13.7%	14.2%	17.5%
	Pre-COVID-19	38.5%	40.8%	49.9%	52.4%	27.3%	33.5%	32.3%	38.4%
10 Ride	During COVID-19	31.2%	32.5%	44.8%	46.4%	23.1%	27.5%	28.7%	33.9%
	Pre-COVID-19	54.1%	55.5%	69.6%	71.0%	43.8%	51.5%	51.5%	59.1%
PAYG Total	During COVID-19	12.1%	12.9%	19.3%	20.4%	8.2%	9.9%	10.8%	12.9%
	Pre-COVID-19	33.6%	35.0%	44.9%	46.3%	26.1%	30.9%	31.2%	36.1%

3.8.3 Alternate Fares: 20/30 and 30/60 Passes

An alternative fare structure is one that is day-agnostic and instead offers trips over a shorter period of time. This type of fare product is often named a “70/90” (in Barcelona) where the first number indicates the number of trips and the second indicates the expiration period. Thus, a 70/90 pass offers 70 trips within 90 days at a discounted rate. This analysis will explore two fare products of a similar structure: a 20/30 (20 trips within 30 days) and a 30/60 (30 trips within 60 days). Both fare products will be analyzed at a 10%, 15%, and 20% discount rate. The idea behind these products are that many mTicket users travel only once per day, taking another mode (such as carpooling) for the return trip. In fact, 65% of all days in which a PAYG user took commuter rail (during the pandemic) were only one trip. This might be a significant reason why many PAYG users choose not to purchase a Flex Pass, which offers unlimited travel for a day.

The two pass designs in this analysis are a 20/30 and 30/60 pass. The 20/30 pass offers 20 trips, equivalent to 10 round trips, within a 30-day period. The 30/60 pass offers 30 trips, equivalent to 15 round trips, in a 60-day period. Both passes are intended to incentivize users to travel more on commuter rail over a given time frame. The current 10 Ride fare product neither offers a discount nor restricts the expiration period. A 20/30 pass would offer a discount compared to 20 PAYG tickets while also restricting the allotted time frame to use the pass. For occasional users who are likely to travel for two weeks in a month, they would be attracted to this pass as it is cheaper than purchasing multiple PAYG tickets. A 30/60 pass has a similar purpose but spread over a longer time frame. This allows less frequent users to take advantage of the discount. Both are intended to be ideal for occasional users but would not provide enough travel for regular Monthly Pass users.

Table 3-12 shows the percent of user-days for the 20/30 and 30/60 pass under a 10%, 15%, and 20% discount for the period before and during the pandemic. Notably, every discount covers a larger user-day proportion of PAYG users than the existing Flex Pass, except for the pre-pandemic user-days on a 20% discount. For example, a 10% discount on a 20/30 pass would be financially beneficial to 16.4% of user-days (34.2% before the pandemic) while an existing Flex Pass is financially beneficial to 12.1% of user-days (33.6% before the pandemic). Similar to the alternate Flex Pass designs, the 20/30 and 30/60 alternate products have an increase in user-days as the discount increases. Interestingly, the user-days are nearly the same before the pandemic for each respective discount between the 20/30 and 30/60 products.

Table 3-12: Percent of beneficial user-days from a 20/30 and 30/60 product design for PAYG users before and during the pandemic

Trips		20			30		
Expiration		30			60		
Discount		10%	15%	20%	10%	15%	20%
One Way	During COVID-19	11.7%	13.1%	14.7%	13.1%	13.9%	15.6%
	Pre-COVID-19	20.5%	22.3%	24.2%	21.4%	22.4%	24.4%
Round Trip	During COVID-19	18.3%	19.8%	21.9%	19.2%	20.2%	22.3%
	Pre-COVID-19	32.6%	34.7%	37.6%	33.1%	34.5%	37.1%
10 Ride	During COVID-19	36.2%	39.4%	43.2%	39.8%	41.7%	45.4%
	Pre-COVID-19	53.8%	57.0%	61.0%	56.5%	58.5%	62.0%
PAYG Total	During COVID-19	16.4%	18.1%	20.1%	18.0%	19.0%	21.0%
	Pre-COVID-19	34.2%	36.5%	39.3%	35.6%	37.0%	39.6%

3.8.4 Post-Pandemic Anticipated Growth

Figure 3-23 shows the estimated number of trips for each alternate Flex Pass design following the methodology from Subsection 3.8.1. The scenarios were estimated from the pre-pandemic and during the pandemic user-days in Subsection 3.8.2. From the user-days, an adoption rate is applied using the current adoption rate from the Flex Pass with some adjustments. Every 5% increase in the discount rate adds 10 percentage points on the adoption rate to reflect the increase in attractiveness of the product. Thus, a 10% discount on the Flex Pass would be a 21.8% adoption rate, a 15% discount would be a 31.8% adoption rate, and a 20% discount would be a 41.8% adoption rate.

The number of monthly trips is highest for the 20% discount on the 5-day Flex Pass at 170,000 in the third scenario. A 10-day Flex Pass at a 20% discount has fewer trips than the 5-day Flex Pass. This makes sense as it offers the same discount but requires more days be taken. Increasing the 10-day Flex Pass from a 30- to 45-day expiration period increases the ridership in Scenario 3 by about 10,000 trips when at a 15% discount and 14,000 when at a 20% discount, which is about an 11% increase. However, increasing the expiration period on the 5-day Flex Pass only increases the trips by about 2% or 3%. These differences in the ridership gain are helpful to understand the potential benefits of changing the number of day passes, discounts, or expiration period.

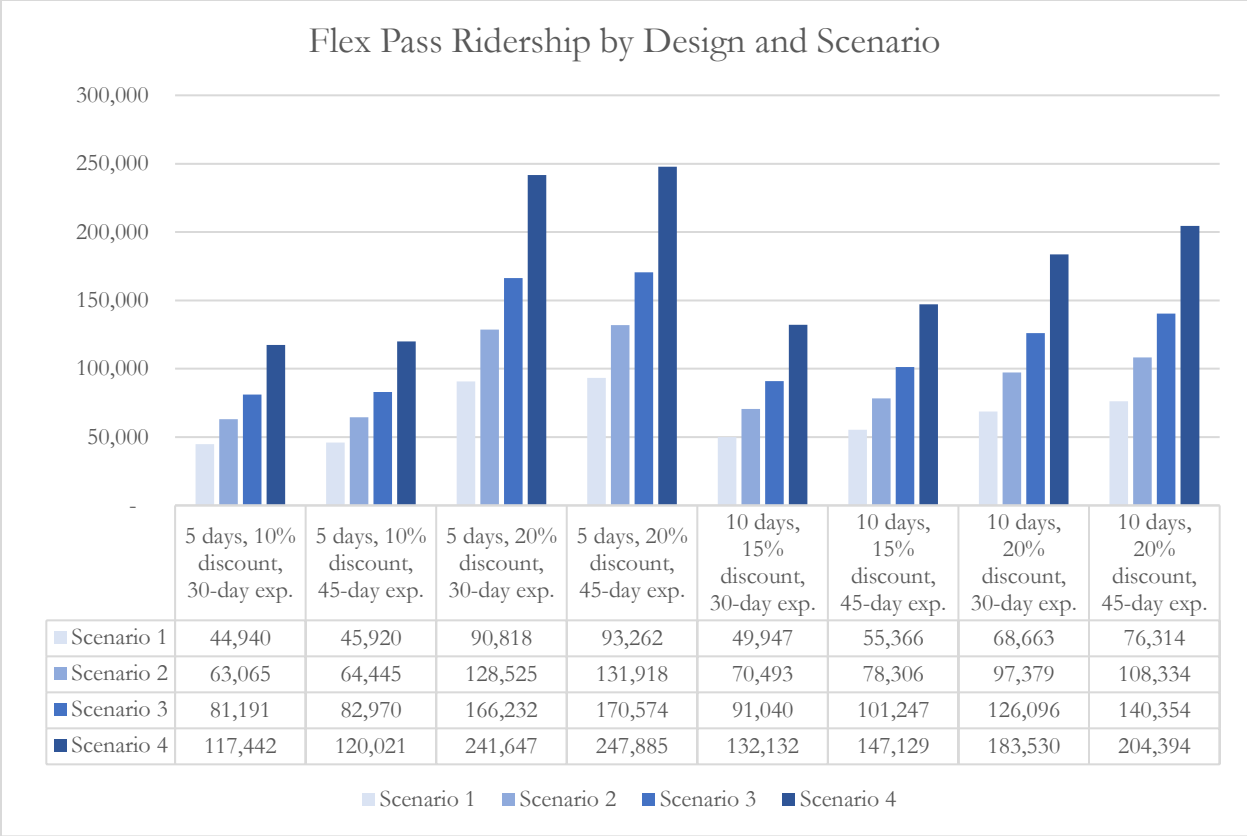


Figure 3-23: Flex Pass ridership by product design and ridership return scenario

Table 3-13 shows the share of trips by Flex Pass design under Scenario 2 for the commuter rail system. The trip market share does not change significantly between scenarios, which is why Scenario 2 is used as the example. Without any changes to the Flex Pass, around 4.5% of all trips would be paid on the Flex Pass in each scenario. However, increasing the discount to 20% would increase the market share to around 9%. Changing it from a 5-day to a 10-day Flex Pass would put the trip market share at around 5-5.5% at a 15% discount and 7-8% at a 20% discount. Note that these estimates only assume a shift in users from PAYG to Flex Pass. It is likely that an increase in the discount would also attract riders who previously took commuter rail but left during the pandemic. Many users might have switched to driving or carpooling during the pandemic and decided the cost and travel time are comparable. Increasing the discount on the Flex Pass would incentivize these passengers to return to the commuter rail system, especially if they commute occasionally.

Table 3-13: Share of trips by fare product and scenario across all of commuter rail

Days	5				10			
	10%		20%		15%		20%	
	30	45	30	45	30	45	30	45
One Way	11.5%	11.5%	10.8%	10.7%	11.5%	11.4%	11.1%	11.0%
Round Trip	13.3%	13.3%	11.5%	11.4%	13.2%	13.0%	12.5%	12.2%
10 Ride	8.1%	8.1%	6.5%	6.5%	7.8%	7.7%	7.2%	6.9%
Monthly	62.6%	62.6%	62.3%	62.2%	62.6%	62.5%	62.4%	62.3%
Flex Pass	4.4%	4.5%	8.9%	9.2%	4.9%	5.5%	6.8%	7.5%

Figure 3-24 shows the estimated number of trips for different product designs that are trip-based for each ridership growth scenario. The process for calculating the trips is the same as above with an additional 10 percentage point increase in the adoption rate for the products being trip-based. The increase in trips from the 20/30 and 30/60 fare products are higher than their respective discount rate for the Flex Pass designs. For example, a 10% discount on a 20/30 pass for Scenario 3 projects around 109,000 trips while a 10% discount for a 5-day Flex Pass projects 83,000 trips (assuming a 45-day expiration period). The 30/60 product has similar estimated monthly trips as the 20/30 product. These trips are not necessarily taken by the same users, as some users might take fewer trips over a longer period while others take fewer over a shorter period. Offering both products might be helpful in capturing both types of commuter rail passengers.

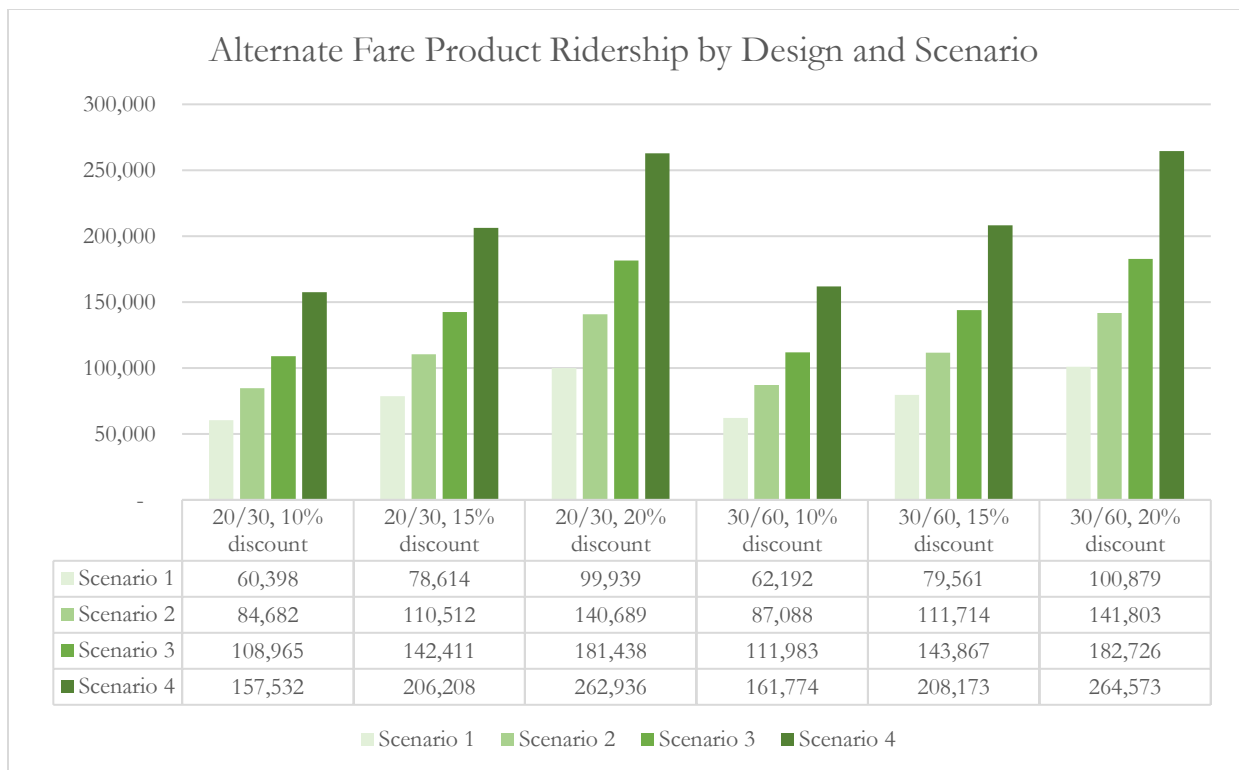


Figure 3-24: Alternate fare product ridership by product design and ridership return

As with the Flex Pass trip market share, Table 3-14 shows the share of trips by fare product and scenario for the alternative fare product (the 20/30 and 30/60). The trip market share for the 20/30 and 30/60 fare products are higher than the Flex Pass for each discount level. At a 20% discount, the 20/30 and 30/60 products would capture almost 10% of the commuter rail users in each scenario. Note that the Perq program accounts for around 40% of the fare revenue on the commuter rail system. While this analysis assumes the fare products are designed for the general public, the Perq program could also incorporate these products into their sale channel. This would yield a higher market share and likely attract more passengers onto commuter rail as these users would receive the pre-tax payroll deductions, which are effectively around an additional 25-35% discount on the product. These alternative fare products are likely to encourage more passengers onto commuter rail, especially at the higher discounts, and will appeal to the occasional commuter.

Table 3-14: Share of trips by fare product in Scenario 2 across all commuter rail

Trips	20			30		
	30			60		
Expiration	10%	15%	20%	10%	15%	20%
One Way	11.1%	10.8%	10.4%	11.1%	10.8%	10.4%
Round Trip	13.0%	12.3%	11.6%	12.9%	12.3%	11.6%
10 Ride	7.6%	6.9%	6.2%	7.5%	6.9%	6.2%
Monthly	62.4%	62.2%	62.0%	62.4%	62.2%	62.0%
Alt Pass	5.9%	7.7%	9.7%	6.1%	7.8%	9.8%

Figure 3-25 combines all the alternate fare products and compares the trip market share by discount level. As can be seen, the share of trips is greatest for the 20/30 and 30/60 pass options, especially at a 20% discount. However, even at a 10% discount, the 20/30 and 30/60 passes have a market share of around 6% while the 5-day Flex Pass only has around 4.5%. A 10-day Flex Pass has the lowest market share, regardless of discount. In fact, a 15% discount on a 20/30 and 30/60 pass is expected to have a greater trip market share than a 10-day Flex Pass at a 20% discount. Even a 45-day expiration period for a 10-day Flex Pass is less attractive than a 20/30 product, which both offer the equivalent of 10 days of round-trip travel. However, as previously discussed, commuter rail passengers only traveled once on 65% of days on commuter rail. Thus, a 20/30 pass is more attractive than a 10-day Flex Pass, even when at the same discount.

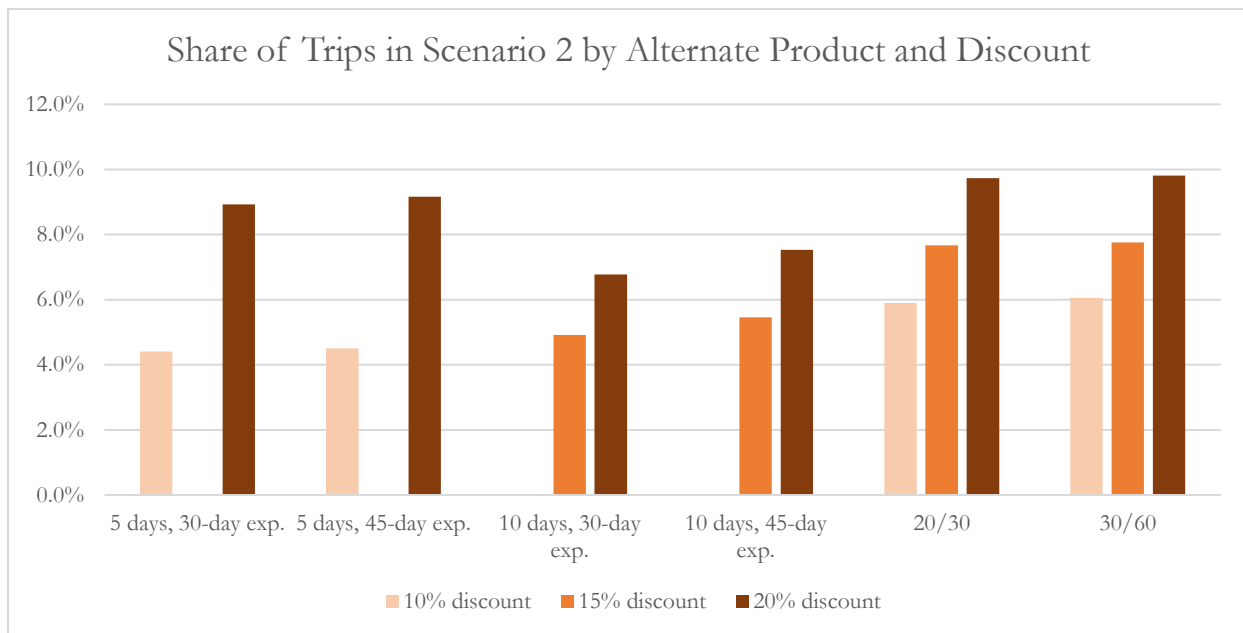


Figure 3-25: Share of trips by alternative fare product design and discount offered for the overall commuter rail system using Scenario 2 as an example

3.8.5 Alternate Fare Product Recommendations and Monthly Pass Impacts

The analysis suggests that the 20/30 and 30/60 products would yield the highest trip market share of nearly 10% across commuter rail when at a 20% discount. Should both products be offered? How much overlap is there between people who would benefit from a 20/30 and a 30/60 product? Of all the users who would benefit from a 30/60 product, 96% of them would also benefit from a

20/30 fare product. However, the reverse is not true, and there are an additional 15% of unique users who would benefit from a 20/30 product but not a 30/60 product. Thus, it would make more sense to adopt the 20/30 instead of the 30/60 fare product. Additionally, the product should be offered at a 20% discount. This would yield the highest share of trips and best incentivize ridership back to commuter rail through a discounted product. As aforementioned, the higher discount would compete with the Monthly Pass. The Monthly Pass is the ideal product to sell, as it offers unlimited commuter rail trips within a given month. To continue to incentivize frequent riders to purchase the pass, the discount on the Monthly Pass should be raised to 30%. How would this discount affect Monthly Pass adoption?

A discount of 30% would put the pass multiple at just below 30 trips, meaning the “break-even” point is at the 30th trip. This would decrease the current cost of monthly passes by around 7-11%, depending on the zone. To calculate the increased adoption of the discounted Monthly Pass, this analysis estimates the proportion of pay-as-you-go users who would surpass the new pass multiple. *Table 3-15* shows the proportion of pay-as-you-go users who currently take more trips than the pass multiple for the Monthly Pass compared to the proportion who would surpass the pass multiple if the discount were at 30%. During COVID-19, an additional 0.5% of users would be within the pass multiple for the Monthly Pass. For the pre-pandemic ridership, an increase of 1.5% of PAYG users would be within the pass multiple under a higher discount.

Table 3-15: Proportion of pay-as-you-go users per month who would reach the pass multiple under a higher Monthly Pass discount

Average Users / Month	During COVID-19		Pre-COVID-19	
	Current	30% Discount	Current	30% Discount
One Way	0.2%	0.5%	0.6%	1.2%
Round Trip	0.5%	1.1%	1.4%	2.9%
10 Ride	2.0%	5.1%	4.7%	10.6%
PAYG Total	0.4%	0.9%	1.4%	2.9%

Calculating the increase in new Monthly Pass purchasers assumes the new users come from the increase in PAYG riders who are now over the pass multiple. This is the difference between the PAYG users over the pass multiple under a 30% discount and without it. The four scenarios are applied to estimate the increase in new Monthly Pass riders. *Table 3-16* shows the process for calculating the new Monthly Pass users and the change in revenue from the 30% discount. First, the number of PAYG users are estimated for each scenario. The difference in new PAYG users surpassing the pass multiple is calculated using the same approach to estimate ridership per scenario. That difference, multiplied by the number of PAYG users, becomes the new Monthly Pass users. Finally, the estimates for existing Monthly Pass users are calculated using the same approach as the ridership per scenario. To calculate the revenue changes, a weighted average of the price of a Monthly Pass is applied to the new users and a weighted average of the change in price with the 30% discount is applied to existing Monthly Pass users. This results (for Scenario 4) in over \$323,000 of monthly revenue from new Monthly Pass users and a drop of \$1,433,000 in monthly revenue for the discounted Monthly Pass. That decrease in revenue is roughly an 10% decrease in monthly revenue, which is estimated to be \$14 Million in Scenario 4. Accounting for the new Monthly Pass revenue, the revenue drop would be around 8%.

Table 3-16: Shift in Monthly Pass users from an increase in the discount to 30%

	PAYG Users	Difference	New Monthly Pass Users	Existing Monthly Pass Users	New Monthly Pass Revenue	Drop in Revenue from Discount
Scenario 1	37,819	0.8%	311	19,252	\$ 80,540	\$ (510,647)
Scenario 2	49,085	1.0%	488	27,942	\$ 126,281	\$ (741,144)
Scenario 3	60,351	1.2%	704	36,632	\$ 182,005	\$ (971,641)
Scenario 4	82,882	1.5%	1,250	54,012	\$ 323,403	\$ (1,432,635)

Note, however, that this analysis did not assume latent demand for the decrease in the cost of a Monthly Pass. The decrease in the cost could attract users from other modes onto the Monthly Pass. Additionally, the lower Monthly Pass price could bring frequent users back to the commuter rail system at a faster rate. Moving from Scenario 1 to Scenario 2 may take less time if the Monthly Pass is at a discount as frequent users and Perq employees (who receive an additional 25-35% discount, not including any potential subsidies from employers) would be further incentivized back to commuter rail. This is an important point as it would yield higher revenue over time as users return earlier on. Furthermore, as will be discussed in Chapter 4, there is the potential to nudge PAYG users and former commuter rail riders onto the 20/30 or Monthly Pass through cheap email messaging from the MBTA.

3.8.6 A Note on Marketing

With any new product, marketing is key to getting a high adoption rate. Many companies spend a significant portion of their operating budget on marketing alone, as a good marketing department can bring in more in revenue than the operating cost of the department. That being said, the MBTA is a public agency that should prioritize implementing a public good that reliably provides transportation access to Greater Boston. However, that should not impede the agency from simplifying the fare product options for commuter rail users. Commuter rail is distance-based, meaning the more zones a user travels through, the higher the cost of the fare. There are 11 zones (Zones 1-10 and Zone 1A) that are each at a different fare and Interzone (IZ) fares for trips that do not begin or terminate in Zone 1A. For Monthly Pass users, they first need to know what zone they will be traveling on, then calculate the per-trip cost that would make a Monthly Pass worth the cost (ignoring IZ and Zone 1A fares, the cost of a Monthly Pass ranges from \$214 - \$426).

Introducing a new fare product, such as the Flex Pass or the 20/30 product, would add further complexity. The MBTA could, however, advertise the products based on passenger travel behaviors. *Table 3-17* shows a simple graphic that displays which product would best match a passenger based on their weekly commute pattern to work. If the user goes to their office only once per week, then a pay-as-you-go ticket would best fit their travel behavior (i.e. One Way or Round Trip). For those who go to the office between two and three days per week, the 20/30 product would best their commuting pattern. Finally, anyone who commutes at least four days per week to work would benefit from a Monthly Pass. This is not a perfect system, as people might commute more some weeks and less others, or they may choose to travel on the weekends. However, commuter rail ridership predominantly travels during the work week and people are likely to know their weekly travel better than their monthly.

Table 3-17: Example of a display showing which products best fit a passenger based on weekly commute patterns

	Days / Week Commuting to Work				
	1	2	3	4	5
PAYG	✓	✗	✗	✗	✗
20/30	✗	✓	✓	✗	✗
Monthly Pass	✗	✗	✗	✓	✓

In advertising the new 20/30 fare product or as they try to nudge users onto Monthly Passes (see Chapter 4:), the MBTA should mention the number of days of work per week that would fit each product. This simplifies the decision-making process for passengers and would make the 20/30 and Monthly Pass more attractive. Beyond advertising, the MBTA could also implement this simple framework in Fare Vending Machines and other sale channels (such as mTicket). This would remind passengers, at the point of sale, of which product might best fit their travel needs. The MBTA does not need to spend a lot on marketing yet could simplify the purchasing process on commuter rail with this implementation.

3.9 Flex Pass, Alternate Products, and Future Implications

This chapter examined the types of users who are most likely to use the Flex Pass as well as exploring what users could have benefited from a Flex Pass but chose to use PAYG instead. Alternate fare structures were explored for a Flex Pass that aims to draw occasional users into a pass structure rather than through PAYG. Overall, a 20/30 and/or a 30/60 pass structure would likely appeal to occasional users and increase pass shares beyond the existing 3% pass share for the Flex Pass. A higher discount rate of 20% would capture more commuter rail users, although it should be paired with a deeper discount (30%) on Monthly Passes. It is still important to keep the Monthly Pass as it offers a zero marginal cost benefit to users who travel often on commuter rail. For the less frequent commuter rail riders, especially those work-from-home more than once per week when they return to the office, a 20/30 or 30/60 fare product would better fit their travel behavior and encourage them to use their trips before the product expires. While the 20/30 and 30/60 passes do not offer a zero marginal cost benefit (once the user travels 20 or 30 times, they have to purchase additional tickets), they are still useful at increasing the ridership by lowering the expiration period from 90 days to 30 and 60, respectively. The 30/60 product overlaps significantly with the 20/30 product, with 96% of users benefitting from both. However, the 20/30 product would reach an additional 15% of users. Thus, the MBTA should focus on selling just the 20/30 product.

Only selling one of the three alternate fare products (Flex Pass, 20/30, and 30/60) also reduces complexity, which would improve marketability of the products. The 20/30 would benefit users who travel two or three days per week for work, while the Monthly Pass at a 30% discount would benefit the users who travel at least four days per week. The marketing of the products by the travel patterns would simplify the decision-making process of choosing a product. Early adoption of the 20/30 product and a higher discount on the Monthly Pass would shift passengers back to the commuter rail system earlier, which results in steady revenue.

Research articles suggest and predict that work-from-home will persist beyond the pandemic, albeit at lower rates than during the pandemic. While the exact proportion of work-from-home “commutes” are unknown, it is likely that ridership will lag for months or years after travel restrictions are lifted. Any amount greater than the share prior to the pandemic will likely affect

Monthly Pass purchases and ridership overall. While the Flex Pass is one option to matching the ridership changes during and after the pandemic, there might be better fare product designs to draw in PAYG users and incentivize ridership. Two potential fare products are the 20/30 and 30/60 passes. These passes offer a fixed number of trips (20 or 30) over a given period (30 or 60 days, respectively) at a discounted rate. Even if the discount is equivalent to a Flex Pass, there would be more PAYG users who would benefit from such a product. Taken together or used separately, the 20/30 and 30/60 passes could encourage users to continue using commuter rail even if they work-from-home half of the time.

Another consideration for the Flex Pass and 20/30 or 30/60 passes is AFC 2.0. While none of the fare product structures are yet determined, AFC 2.0 will allow the MBTA to incorporate new features in fare product design and transfer rules. For instance, currently there is no method for mTicket users to transfer to a bus or subway, which is why they receive a \$10 discount on Monthly Passes. However, under AFC 2.0 there will be fare integration across all modes, although the exact ruleset for how transfers will be applied is not yet decided. AFC 2.0 could also include “fare capping” across the whole system. Fare capping is a fare structure where users purchase individual trips but are “capped” at a certain rate at the end of each week and/or month. For example, if a trip costs \$2 and a Monthly Pass costs \$70, fare capping would remove the Monthly Pass and charge users per trip until they reached \$70 for the given month. Any additional trip would be free until the end of the month. Fare capping has significant implications on all passes as it effectively makes them null. While all fare alternatives would be affected by a fare capping structure, it is still important to recognize the implications of such a design before instituting it.

This analysis focused on the Flex Pass and alternate designs for the flexible fare product for commuter rail. While the mTicket provides a platform for quickly rolling out new fare products, the 20/30 and 30/60 products could be incorporated into the other sale channels on commuter rail. Additionally, the products could be introduced into the bus and subway system. However, a closer analysis on the impacts of rolling out the 20/30 and 30/60 pass to the bus and subway system should be explored. Nonetheless, introducing a flexible product for occasional users, which is anticipated to be a larger share of transit riders post-pandemic, would meet the travel behaviors of less frequent riders.

While the Flex Pass has been used primarily by previously Frequent, Occasional, and Peak users, it has only managed to capture 6% of the market share. Part of the reason for this low market penetration could be because 65% of user-days traveled only once per day on PAYG, lowering the interest in using day passes. Instead, the MBTA could offer a different fare product, such as a 20/30 or 30/60 pass, which still restricts the availability of use while also offering a discount to PAYG users. This alternate fare product is expected to have a greater market share of commuter rail users. However, another potential reason for the low market share could be due to poor marketing, given that the Flex Pass was introduced during the middle of a pandemic. Chapter 4: examines potential methods to increase pass purchases that could be used on the Flex Pass or alternate version.

Chapter 4: Nudging Users to Pass Products to Induce Ridership

Chapter 3: illustrated a new pass product that was offered at the MBTA during the COVID-19 pandemic and alternative passes that could be designed as alternatives. However, pass sales on the Flex Pass only accounted for 6-7% of mTicket sales, which is in turn only a third of commuter rail revenue. Flex Pass adoption may have been low due to the small discount provided (not enough incentive for people to switch) or because of insufficient marketing. Given that the product was introduced and advertised in the midst of a global pandemic, it makes sense that knowledge of the new product might not have reached all commuter rail riders. This chapter describes an email marketing campaign that occurred in the fall of 2019 with the intention of increasing pass sales on mTicket that perhaps could be adapted to increase Flex Pass sales in the future.

This chapter is divided into 5 sections. 4.1 discusses the motivation for this chapter in more detail. 4.2 explains what randomized control trials are and how useful they are in research applications. 4.3 and 4.4 analyze two case studies that were conducted in the Fall of 2019. Both case studies target pay-as-you-go (PAYG) users and attempts to nudge them onto passes through targeted email campaigns. The first case study (4.3) advertises the Monthly Pass to frequent PAYG users. The second (4.4) focuses on leisure travel by highlighting the Weekend Pass. The importance of focusing on passes is to provide the zero marginal cost benefit to more passengers. The final section (4.5 Implications of Campaigns) summarizes the findings of the two case studies and considers their implications in helping capture ridership as the pandemic subsides, the possibilities under AFC 2.0, and the overall usefulness of email marketing campaigns.

4.1 Motivation for Nudging Users to Passes

As discussed in *The Monthly Pass for the Reluctant Commuter Rail Rider*, mTicket sells primarily PAYG tickets and only a portion of monthly passes. However, passes are beneficial to increasing ridership as each additional trip is effectively free throughout the duration of the pass. This incentivizes users to increase their frequency of use in order to “get their money’s worth.” Since passes constitute a smaller portion of mTicket revenue than PAYG tickets, the pool of potential monthly pass users is much higher on mTicket. If the MBTA is able to nudge a few users onto Monthly Passes, that will provide zero marginal cost benefits to PAYG users, potentially increasing their ridership and providing a more stable month-to-month revenue stream. If successful, email marketing campaigns could be used to shift users into new fare products that better fit their travel behaviors. Additionally, email marketing campaigns could help nudge transit users to passes as travel restrictions are lifted and offices reopen.

Email marketing campaigns are quite useful as they are usually low-cost options for agencies to use to attract ridership. However, since the great majority of the MBTA fare collection system is card-based, there is no way to relate a card to an identifiable email address. mTicket is account-based, however, and therefore has an email associated with the user account. Thus, sending an email encouraging users to purchase passes only requires a quick analysis on the targeted users (to avoid spamming users who are not active or unlikely to purchase a pass) and a staff member to draft an email.

The purpose of this study is to nudge PAYG users onto passes, targeting those with travel behaviors that are near the cost of a monthly pass. At the time of conducting this experiment, there were two available passes as the targets of these email marketing campaigns – the Monthly Pass and the Weekend Pass. While the Monthly Pass provides the best revenue stream per user and highest ridership per user, the Weekend Pass is a bargain and, in most cases, a cheaper fare product than PAYG tickets on the weekend. Additionally, passes in general offer a zero marginal cost benefit, which encourages users to ride more often than they might have otherwise had they paid for each individual trip.

4.2 Randomized Controlled Trials (RCTs)

A randomized controlled trial is often viewed as one of the most effective methodologies for cause and effect analysis. Medical disciplines use RCTs widely in their research as it is viewed as the “gold standard.” With improved technology and passive data collection systems, RCTs are becoming increasingly popular in other fields. In fact, in 2019 two MIT and one Harvard professors won the Nobel Prize in Economic Sciences after conducting RCTs to better understand how interventions by NGOs can improve low-income communities (Dizikes, 2019).

So what is a randomized control trial? RCTs are experiments that are conducted in a controlled environment where one group is provided a treatment of some sort and the other, which is considered the “control” group, is not offered the treatment. In medicine, the “control” group is often offered a placebo and are “blind” from whether they are in the control or treatment group. This prevents the users from knowing whether they were given the treatment or nothing during the trial. Research has since found that people have positive responses to the placebo, naming this the “placebo effect.” This effect shows that people who think they might be given a treatment have positive effects on their health even when no treatment was given.

The two email marketing campaigns in this chapter are designed as RCTs where users are divided into two groups, a control and a treatment. However, unlike medical RCTs, the control group is unaware that they are part of a study. This is because the control group consists of random mTicket users (who match the qualifications of the treatment group) and are only observed based on their revealed choices. While the treatment groups were also unaware of the study, they received an email informing them of the financial benefits of the pass products. Using both a control and treatment group is done to understand what the counterfactual would be. For example, if mTicket users were given an email and there was no control group, then there would be nothing to compare the pass purchase rate to. Having a control group that is not involved in the intervention provides a counterfactual that answers “how many passes would have been purchased had an email not been delivered?” Through statistical tests, researchers can then answer how effective an intervention is at producing different results from the counterfactual.

4.3 Monthly Pass Campaign

The Monthly Pass campaign aims to increase Monthly Pass sales among heavy-use pay-as-you-go ticket users. The hypothesis is that there are mTicket pay-as-you-go users who are traveling frequently enough to where a Monthly Pass might be financially beneficial to them. By sending an email to these users with information on the financial benefits and convenience of a monthly pass, users would be more likely to purchase a Monthly Pass. This section will explain the design of the Monthly Pass email campaign and the results from the experiment.

A reminder that this experiment uses the mTicket app, which is a sale channel within commuter rail but provides an account-based fare collection system for disaggregated analyses. The immediate data collection (mTicket data is uploaded to the data warehouse every night) provides up-to-date information that can be used to target individuals based on their travel behaviors. This experiment targets high frequency users in the interest of shifting them to Monthly Passes. The experiment was conducted at the end of September 2019 with the intent of increasing October Monthly Pass sales.

4.3.1 Segmentation of Targeted Users

While all mTicket users could be sent the informational email, this could lead to abuse of the email marketing platform and create “spam” in the minds of the users. Instead, it is better to target users who are most likely to interact with the email. A targeted email approach allows the transit agency to run multiple email marketing campaigns at the same time without spamming all mTicket users. In this experiment, the target group consists of the frequent commuter rail riders on mTicket who primarily purchase PAYG tickets. After running a sensitivity analysis, it was decided that “frequent” ridership was defined as taking at least 24 trips in a month. Note that the pass multiple for commuter rail is around 32 (differs by zone), so the 24 threshold is roughly 75% of the pass multiple.

There is the question of how far back should riders who were considered “frequent” be considered? The first consideration was just for the most recent month (September 2019). Those who traveled at least 24 trips would be targeted. However, since people are likely to fluctuate in the number of trips they take each month, it was important to include users who may have been frequent in previous months but went on vacation in September 2019 or just happened to travel less. This was especially important as September is a common month for vacation travels. To be sure these users were included, a “consistent” segment was included. The “consistent” group is categorized as all users who traveled at least 24 times in any three months between March and August 2019. Therefore, they are “frequent” at least half of the months leading up to the email marketing campaign.

The “consistent” group was further divided into two groups: a Consistent Recent and Consistent Non-recent” group. The difference between the two groups depends on their ridership in September 2019. If the user took commuter rail at least 24 times in September, they would be categorized as Consistent Recent. Otherwise, they are considered Consistent Non-recent. While the Consistent Non-recent group did not travel much in the month leading up to the email campaign, they were still an important group to target since it is possible they only decreased their usage temporarily, as might happen from those who take a vacation.

Furthermore, there are two additional groups that are defined only by their recent activity. The first is the Above group, which is defined by users who rode commuter rail at least 32 times in September. This, in most cases, means they traveled more than the pass multiple for a monthly pass. Essentially, these users would have benefited financially had they purchased a monthly pass rather than PAYG tickets.

The final group is the Near segment. These users traveled at least 24 times in September but less than the pass multiple of 32. While these users benefited financially from purchasing PAYG tickets rather than a Monthly Pass, they might still be interested in a Monthly Pass that provides convenience (they would not have to purchase each individual ticket) and zero marginal cost. On top of that, they might be increasing their commuter rail usage and could benefit from a Monthly

Pass. Both the Above and Near segments do not include consistent users, meaning that each of the four groups are mutually exclusive from each other.

Table 4-1 shows the number of accounts that fit into each of the four groups for September 2019. The original plan for the experiment was to send an email to 500 accounts in each group and observe 500 accounts as the control. However, for various reasons the final number of accounts in each group vary in size between 341 and 584. Since the email had to be sent in September with enough time for the users to see the email and purchase a pass before October, the size of each group and valid accounts had to be estimated. Additionally, mTicket, while the most immediately updated fare collection system at the MBTA, only updates its data once a day overnight, meaning group assignments had to be created with data updated the day before sending the email. To estimate each group size, the ridership cutoffs were scaled down based on the number of weekdays that occurred since the mTicket data was last updated out of all weekdays that month.

Table 4-1: Total number of accounts that are described by each of the targeted groups.

Target Group	Count
Above Recent	870
Near Recent	3482
Consistent Recent	2629
Consistent Non-Recent	2745

Once the groups were estimated, the accounts in each group were randomly divided into a control and a treatment group. The randomization of the control and treatment groups are an important component of RCTs. The treatment group received an email that shared information on a Monthly Pass for the zone they most frequented that month (see 4.3.2). However, since these groups were estimated before the end of the month, the final group definitions were determined after the end of the month and not all groups had perfectly even sizes in the control and treatment groups.

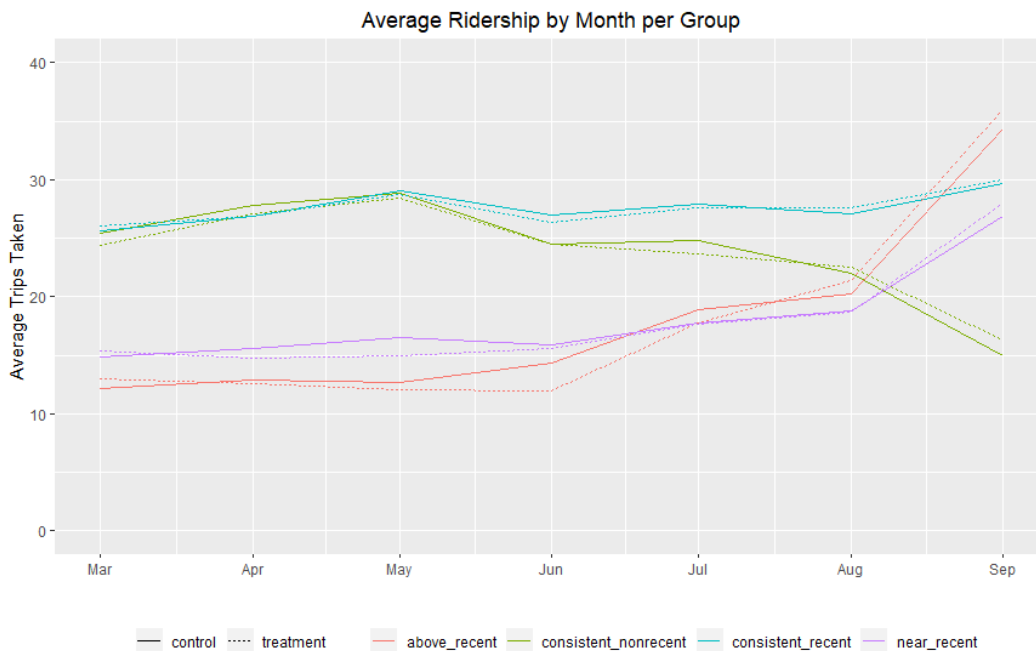


Figure 4-1: Average total trips on mTicket for each group. CR = Consistent Recent. CN = Consistent Non-recent.

Figure 4-1 shows the average ridership for each group. Recall that the control group consists of mTicket users who have similar behaviors as the treatment group but were never sent an email. While all of the accounts were randomized into either a treatment or control group, it happens that the treatment groups all had slightly higher ridership than the control groups in each group. However, the ridership trends of the control group had higher ridership from previous months than the treatment. Overall, average ridership fluctuated each month between the control and treatment groups.

4.3.2 Email Design

The email was identical for all target treatment groups but individualized to each user. Each user in the treatment group received an email as shown in Figure 4-2. Information about the cost of a Monthly Pass (“M_pass_price”) for the most common zone fare traveled (“maxzone_mostfrequent”) by the individual is included. Additionally, a link to the MBTA commuter rail fares webpage was included for further information. While the zone traveled by the user is targeted, no other identifiable information was included in the email, as the email is introduced with “Hello Commuter Rail Rider.”

To provide an avenue for direct feedback, the message includes an email address at the MBTA that is dedicated to responding to mTicket questions. It also personalizes the email to avoid making it appear like a spam message by including the first name of an MBTA staff member. Finally, a “Was this message helpful? Let us know” binary thumbs up or down function was included at the bottom to promote quick feedback on the email effectiveness. A generic screenshot of the mTicket app is included in the email to show the fare products on mTicket.

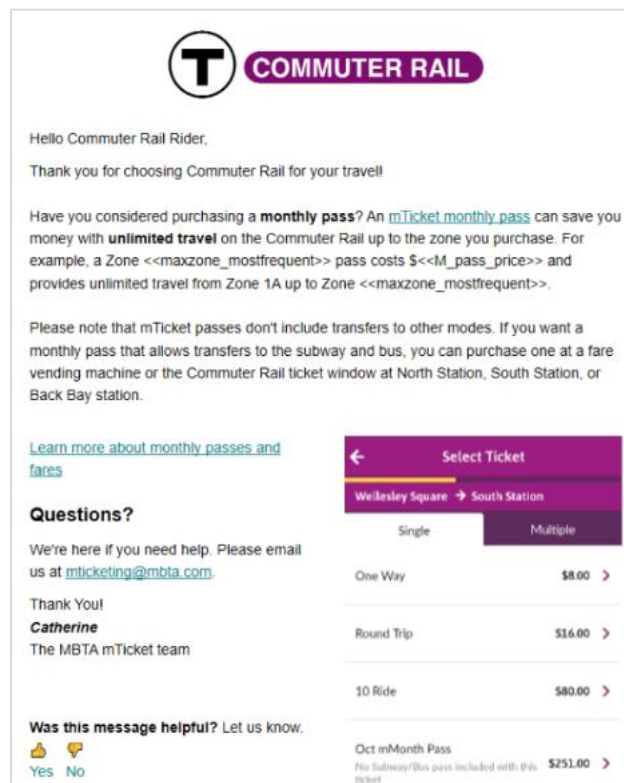


Figure 4-2: Email example from the Monthly Pass email marketing campaign. Each email was catered to the travel behaviors of the email recipients.

4.3.3 Monthly Pass Campaign Results

Table 4-2 shows the number of passes purchased by each segment by the treatment and control groups. As anticipated, the Above group had the highest proportion of passes purchased with 17.3% of the treatment and 15.7% of the control purchasing an October Monthly Pass. Additionally, each treatment group had a higher percent of the group that purchased a Monthly Pass compared to the control. However, the higher proportion of pass purchases does not guarantee that the email campaign was the reason for the higher pass purchases. While each treatment group does have a higher pass purchase rate, the differences between the treatment and control are small.

Table 4-2: Pass purchases in October 2020 and total accounts in each group.

Updated Email Groups	Sample			Control		
	# Passes	Total	Percent	# Passes	Total	Percent
Above Recent	59	341	17.3%	75	477	15.7%
Near Recent	39	348	11.2%	45	486	9.3%
Consistent Recent	19	584	3.3%	11	512	2.1%
Consistent Non-recent	25	406	6.2%	24	497	4.8%

To understand whether the email marketing campaign was the reason behind the increase in pass purchases, a 2-Proportions test is run on each treatment and control pair (equations for the 2-Proportions test can be found in 2-Proportions Test). Table 4-3 shows the results of the 2-Proportions test. P-values below 0.05 are considered statistically significant and would suggest that the email marketing campaign was the reason behind the higher pass purchasing behavior in the treatment groups. However, no segment had a p-value below 0.05, and therefore the increase in pass purchases cannot be attributed solely to the treatment.

Table 4-3: Results of the 2-Proportions test on each group

Group	Treatment %	Control %	p-value
Above Recent	17.3%	15.7%	0.274
Near Recent	11.2%	9.3%	0.178
Consistent Recent	3.3%	2.1%	0.132
Consistent Non-Recent	6.2%	4.8%	0.190

However, the open rate from these emails was only 40% and the click rate (on the links) was significantly lower, at just around 2.5% of all users who were sent an email. Since over half of the users never opened the email, it makes sense that the increased pass purchase rate from the treatment was not statistically significant. Thus, the 2-Proportions test was repeated on just those users who opened the treatment email. Figure 4-3 shows the proportion of users who purchased a Monthly Pass in the control and those in the treatment who opened the email. Considering only those who opened the email, the Consistent Recent and Near groups were statistically significant in the addition of users who purchased a Monthly Pass (both with a p-value below 0.05).

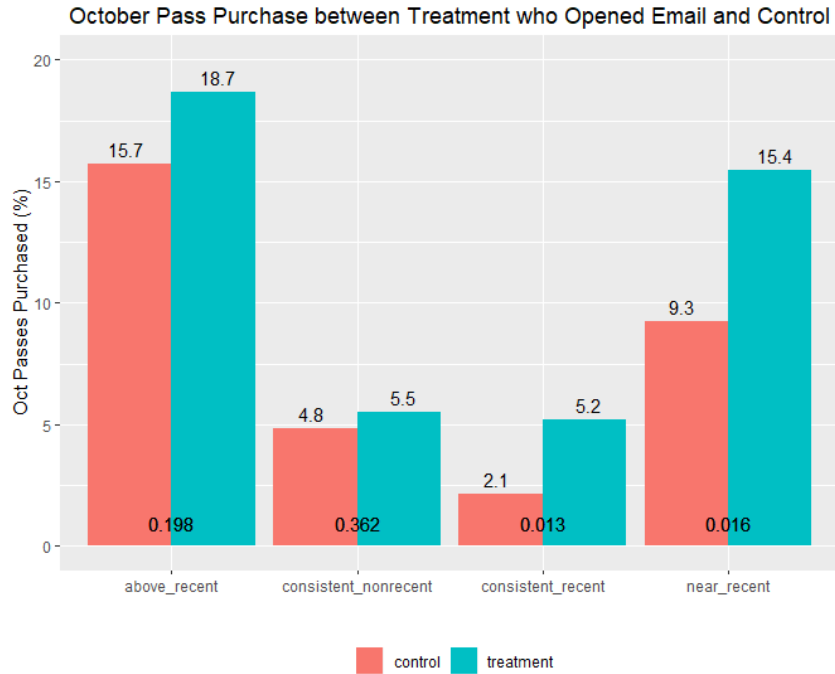


Figure 4-3: Percent of each group that purchased an October Monthly Pass separated by those in the treatment that opened the email and the control. The p-value is shown at the bottom of the bar graphs.

The Near and Consistent Recent groups were most affected by the email treatment, while the Above and Consistent Non-recent groups – still having an increase in pass purchases – were less affected by the email marketing campaign. This could be because those who were in the Above and Consistent Non-recent groups have already decided either on purchasing a pass or sticking to PAYG tickets. One of the comments received from someone who received an email indicated that they purposefully avoided purchasing Monthly Passes as they were able to avoid paying fares when the trains get overcrowded and conductors are unable to check passenger tickets. While this fare evasion is evident and known to the MBTA, the fare validation process is conducted by Keolis, the commuter rail train operator. Another user indicated that they take alternative modes to work and prefer not committing to a Monthly Pass out of uncertainty of reaching the pass multiple.

While these increases in monthly pass sales may appear minimal, they impact a large portion of revenue from mTicket. In total, all four groups account for just over 20% of the mTicket revenue for September 2019 (Table 4-4) *Table 4-4: Impact on revenue and ridership from the four groups targeted in the Monthly Pass Campaign.*, despite only accounting for 7% of the users. The largest groups (in terms of ridership and revenue) are the Near and Consistent Recent groups. These are also the groups that were most affected by the email marketing campaign. Shifting these users to Monthly Passes should help increase ridership by providing the zero marginal cost. Long-term effects of switching people to Monthly Passes is not known, and the COVID-19 pandemic occurred a few months after this campaign, which greatly impacted ridership and Monthly Pass sales.

Table 4-4: Impact on revenue and ridership from the four groups targeted in the Monthly Pass Campaign.

September	mTicket Total	Above Recent	Near Recent	Consistent Recent	Consistent Non-Recent	Total	% of Total
Accounts	139,459	809	3,425	2,567	2,701	9,502	6.8%
Trips	1,037,118	28,126	91,542	75,977	28,480	224,125	21.6%
Revenue	\$9,076,716	\$246,406	\$790,478	\$645,447	\$245,086	\$1,927,416	21.2%

4.4 Weekend Pass Campaign

The Weekend Pass campaign was designed to both increase ridership while also advertising the leisure travel potential on commuter rail. Commuter rail is primarily used for commuting and rarely used for leisure travel. However, there are many tourist destinations along the commuter rail line. Given that Greater Boston is one of the oldest cities in the United States, there are many historic towns in the area. Since rail developed around historic towns, many of these destinations are connected by commuter rail. Plymouth, Massachusetts, the location of the Mayflower landing, is a terminal station on a commuter rail line (the Kingston/Plymouth line, to be exact). Similarly, Rockport, Newburyport, and even Providence, Rhode Island are all destinations on the commuter rail system. Figure 3-12 from Chapter 3: shows how weekend users are most likely to travel to Zones 8-10, which include the tourist destinations mentioned above. Even still, 75% of commuter rail trips occur during the peak hour and over 95% happen on weekdays. Thus, capacity is rarely an issue on commuter rail on the weekend and increasing weekend ridership is a broad goal for the agency.

The Weekend Pass is a financial bargain for almost all commuter rail zones. A pass costs only \$10 and provides unlimited travel on the weekend. For any passenger who travels at least twice on the weekend (at least one round trip), the Weekend Pass is cheaper than all zone fares except Zone 1A (which is priced at \$2.40, the equivalent of a trip on the subway). The only other exceptions are for reduced-fare trips (i.e. senior, disabled, school children, and low-income youth between 18 and 25 years old) and Interzonal fares. These two fare products make up a small portion of the mTicket user-base and still benefit from a Weekend Pass if they travel beyond five zones.

4.4.1 Leisure Campaign Design

The email marketing campaign to increase Weekend Pass use, called the “Leisure Campaign” for short, is designed to advertise the Weekend Pass for those who might be unaware of it while simultaneously nudging users to purchase a Weekend Pass and use commuter rail to travel on the weekends. The hypothesis of the campaign is that an email advertising the leisure activities in Greater Boston will increase the Weekend Pass purchases. Three weekends were targeted in the campaign with the first email being sent out on Thursday, October 24th and the last being delivered on Friday, December 6th. Since three emails were delivered, targeted users were divided into two groups: those who received a single email and those who received multiple emails (one for each weekend).

The experiment divided users into five total groups: Control, Multiple, Email 1, Email 2, and Email 3. The “Multiple” group received all three emails while the “Email #” groups represent users who received only one email of the three (Email 1 received the first email, Email 2 the second, and Email 3 the third). The first email, which was sent out on Thursday, October 24, advertised Salem, Massachusetts. Salem is known for the Salem Witch Trials from the 1690s and is often packed with tourists around the Halloween holiday season. The second email was sent out on Friday, November 8 and advertised professional sporting events, concerts, and other events at TD Garden in

downtown Boston (located at North Station, one of two terminal stations in downtown Boston for commuter rail service). The third email was sent out on Friday, December 6 and showcased Wachusett Mountain, a ski mountain with a shuttle service to the Wachusett commuter rail station. The messaging on the emails was intentionally designed to showcase seasonal events that occurred around the time of distribution.

In any experiment, it is important to get a significant sample size to validate the results of the experiment. While tens of thousands of accounts could have been emailed for this experiment, the MBTA was cognizant to avoid sending mass emails to all mTicket users. In the end, it was decided that the control group would consist of 1200 users, the multiple group would contain 600, and each 'email #' group would include 200 users. This comes out to a total of 1200 users in the control and 1200 users in the treatment groups.

Similar to the Monthly Pass Campaign, the email campaigns are more effective when they are targeted to users who are likely to purchase the pass. For a Weekend Pass, the pool of potential candidates is much greater as any non-Monthly Pass holder would benefit from a Weekend Pass. However, it is important to include only users who are somewhat active on mTicket. The requirements for the control and treatment groups are that all of the targeted users have taken at least one trip in two of the previous three months to ensure they have had recent activity on the commuter rail system. The only other requirement is that none of the users currently possess a Monthly Pass. Users who have a Monthly Pass have no reason to purchase a Weekend Pass as they already have unlimited travel available for that month.

4.4.2 Email Designs

As previously mentioned, three emails were delivered just before three separate weekends to encourage leisure travel through the Weekend Pass. The first email, shown in Figure 4-4 and delivered on Thursday, October 24th, 2019, highlights the Halloween festivities at Salem, MA. Salem is the location of the infamous Salem Witch Trials and has since become a major tourist destination around Halloween. As the MBTA already provides additional service to Salem to accommodate the increased travel, this email notification helps nudge users to take commuter rail to Salem, rather than drive or take another mode. The email also highlights the \$10 Weekend Pass and the “unlimited travel” provided by the pass to further incentivize the pass purchase. Note that the “Haunted Happenings” special event pass is just a holiday-branded version of the Weekend Pass and is functionally the exact same.



Take the T to Salem this weekend

Enjoy the best of fall in New England with a trip to [Salem's Haunted Happenings](#).

We're running extra [trains to Salem](#) this weekend. And take advantage of **unlimited travel** with the [\\$10 weekend pass](#) to enjoy other fall hot spots by Commuter Rail.

If you're visiting Salem on the 31st, we have a treat! A *Haunted Happenings* special event pass will get you there and back for just \$10.

Enjoy the weekend!
Catherine
The MBTA mTicket team



Figure 4-4: First email in the Leisure Campaign, that was delivered on Thursday, October 24th, 2019, features Salem, MA and the Halloween festivities in the town.

The second email, shown in Figure 4-5, was delivered on Friday, November 8th, 2019 and advertised events that were happening at TD Garden, an events venue located in North Station. TD Garden was highlighted partially as an example of the types of events that occur on the weekends in Boston but also because it is located in North Station. The northern commuter rail lines all terminate in North Station, which houses TD Garden above the commuter rail tracks. This makes taking commuter rail an attractive option as it is significantly cheaper than paying for parking in downtown Boston and takes passengers directly into the venue. However, the nudging factor may not be as useful if people are unwilling or not interested in attending any events at TD Garden. Conversely, all commuter rail lines terminate in downtown Boston, making it more accessible than stations such as Salem, which is only accessible on the Newburyport/Rockport line.



Take the T to TD Garden



The Celtics and Bruins are back!

Located just above [North Station](#), a hub for Commuter Rail and subway service, [TD Garden](#) is home to some of Boston's most popular events. The Celtics and Bruins are back in full swing, and this Saturday, [Comics Come Home](#) is at the Garden, featuring Denis Leary, John Mulaney, and more. Driving can be a hassle, so **skip the traffic and take the T!**

Heading to the city for a weekend event? Get **unlimited weekend travel** on the Commuter Rail with the [\\$10 weekend pass](#).

Enjoy the weekend!

Catherine

The MBTA mTicket team

Was this message helpful? Let us know.



Figure 4-5: Second email in the Leisure Campaign sent on Friday November 8th, 2019. This email advertised events that occur at TD Garden in downtown Boston, a major sports and events venue located in North Station.

Finally, the third email, delivered on Friday, December 6th, 2019 and shown in Figure 4-6, advertises Wachusett Mountain, a ski resort with shuttle service to the Wachusett commuter rail station. The email highlights the additional service provided on the Fitchburg line to take people to Wachusett as well as the free shuttle provided by Wachusett Mountain. Additionally, information on departures and arrivals from North Station to Wachusett and back are included on the email. As with the other emails, the \$10 Weekend Pass is highlighted for its unlimited trips and cheap price.



Take the T to Wachusett Mountain



Photo courtesy of Wachusett Mountain

Winter Ski Train

Did you know you can take the Commuter Rail to Wachusett Mountain? On Saturdays and Sundays during ski season, the MBTA runs special trains on the Fitchburg Line from North Station that are equipped with ski and snowboard racks. Wachusett Mountain also provides a [free shuttle from the station](#) to the slopes for designated trains.

Starting December 7, 2019, the weekend ski train runs on Saturdays and Sundays according to the schedule below. Make sure you purchase an unlimited [\\$10 weekend pass](#) to get the best price on your trip!

North Station to Wachusett:

- Depart North Station: 8:35 AM
- Arrive at Wachusett Station: 10:11 AM
- Free shuttle to the mountain

Wachusett to North Station:

- Free shuttle to Wachusett Station: 5:15 PM
- Depart Wachusett Station: 6:10 PM
- Arrive at North Station: 7:41 PM

Enjoy the weekend!

Catherine

The MBTA mTicket team

Was this message helpful? Let us know.



Figure 4-6: Third email delivered on Friday, December 6th, 2019. This email advertises Wachusett Mountain, a ski resort with shuttle access to the Wachusett commuter rail station.

4.4.3 Leisure Campaign Results

Figure 4-7 shows the percent of accounts in each group that purchased a weekend pass for each week in the trial period. Due to smaller group sizes, the single email treatment groups (Email 1, 2, and 3) had higher variability in pass purchasing each week. For that reason, all treatment groups are combined in Figure 4-7. The trial period begins two weeks before the first email was sent out and ends the weekend after the last email was sent out. Emails were sent out on the 3rd, 5th, and 9th weekends. The control group shows a downward trend each week as the weather became increasingly colder. This matches the general Weekend Pass sales trend where monthly sales are highest in the summer and lowest during the winter months.

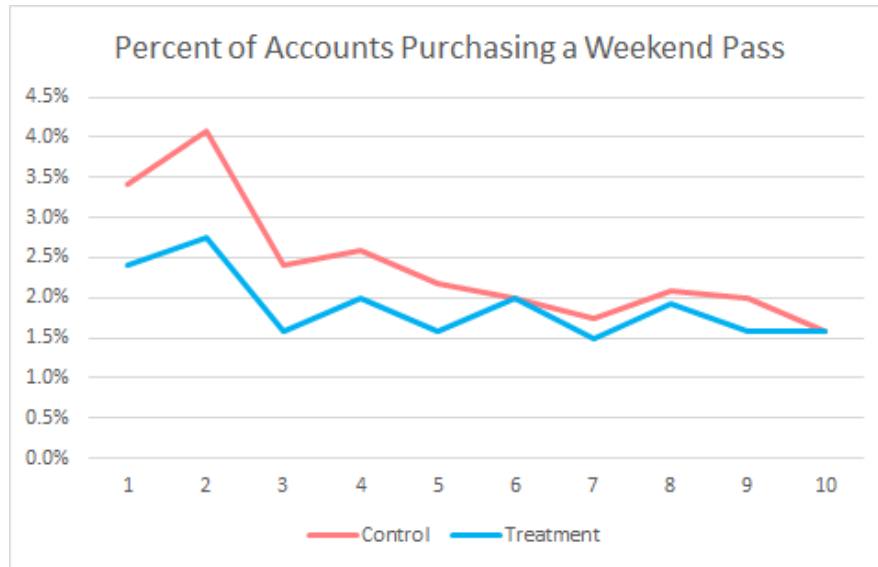


Figure 4-7: Proportion of accounts purchasing a weekend pass during the Leisure Campaign. The first weekend corresponds with October 12-13, 2019 and the 10th (last) weekend corresponds to December 14-15, 2019.

A Difference-in-Differences (DiD) approach was used to determine whether the emails had any effect on weekend pass purchasing. DiD uses the control group to estimate the trend and compares the deviation from the trend from the treatment group. The DiD looks at the difference between the groups (i.e. control vs multiple) before and after the treatment to see the trends. Figure 4-8 shows an example of the DiD approach. In the example case, the control group had a natural decline in percent of passes purchased between the before and after periods. This decline would theoretically correspond to a similar decline from the treatment group. However, due to the intervention, the treatment group deviates from the trend and shows a positive growth based on the intervention.

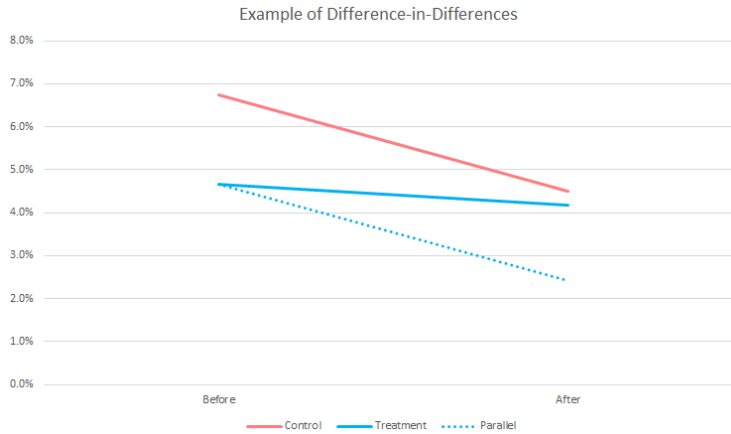


Figure 4-8: Example of Difference-in-Differences (DiD). The trend of the control is matched for the treatment ("Parallel") and any deviation from this trend indicates a shift by the treatment group.

Figure 4-9 shows the results of the DiD approach between the control and treatment, separated by the number of times they received an email (Single vs Multiple). Looking at the first email sent in comparing the control to multiple groups, the control had 6.8% of accounts purchase a weekend pass in the two weeks prior to the email whereas the multiple group had 4.7% accounts purchase a pass. This difference (-2.1%) marks the difference in groups prior to the intervention. After the intervention, the control dropped to 4.5% of accounts purchasing a weekend pass in the following two weeks whereas the multiple group only dropped to 4.2%. This new difference (-0.3%) is noted. The DiD is the difference of these differences of $-0.3 - (-2.1) = 1.8\%$. The sign of the DiD is important, since it indicates whether the treatment showed an increase or decrease in pass purchasing. In this case, the multiple group saw a higher percent of accounts purchase a weekend pass than the control.

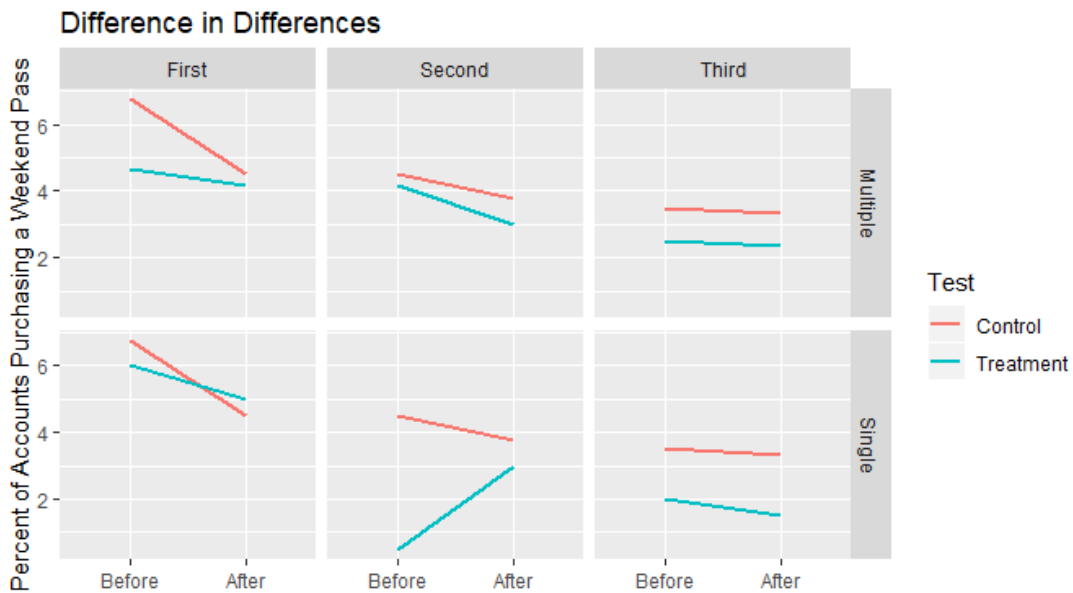


Figure 4-9: Difference-in-Differences between the control and treatment groups, separated by those who received all three emails (Multiple) and those who received only one email each week (Single).

The before and after analyses each included two weekends. This was because the proportion of weekend passes purchased each weekend is so low and only declined as the winter progressed. Including two weekends before and two weekends after the email intervention provided a more stable shift in purchase behavior. Each email, separated by their respective group (Multiple or Single), is compared it to the control group and the DiD results are shown in Table 4-5. The first email (Salem, MA) had a positive DiD between the Multiple and Single compared to the control group. This means the intervention increased Weekend Pass sales by 1.8 and 1.3 percentage points in the Multiple and Single groups, respectively. The second email (TD Garden) had mixed results, with the Multiple group having a decrease in Weekend Pass purchases while the Single group had a 3.3 percentage point increase. However, the high increase in the Single group should be taken with caution as the two weeks prior to the intervention only had around 0.4% pass purchase rate, which was significantly lower than the control (around 4.5%). Comparing single emails to the control, the first and second email saw considerable increases in weekend pass purchases (1.3% and 3.3%) while the third email saw a decrease (-0.3%), which might be due to the third email being sent out in December, where there are less weekend pass purchases in general (since it is the winter).

Table 4-5: DiD results from the Leisure Campaign

Control vs.	Multiple	Single
First Email	1.8%	1.3%
Second Email	-0.4%	3.3%
Third Email	0.0%	-0.3%

4.4.4 Implications of Leisure Campaign

In general, the email intervention appeared to work best closer to the summer and had less of an effect later on in the winter. Additionally, sending multiple emails to accounts did not appear to increase the chances of purchasing a Weekend Pass. Thus, future leisure campaigns should focus on new groups of users each week and prioritize the summer weekends over the winter.

The Weekend Pass still constitutes a small portion of overall commuter rail revenue. While an email marketing campaign shows promise of increasing pass sales, it is unlikely to cause a drastic shift in ridership. Instead, a more probable way of increasing ridership on commuter rail would be through what has been labeled a “Regional Rail” approach. “Regional Rail” is the concept of modernizing the commuter rail system and increasing frequency to closer match the bus or subway system. It takes inspiration from the RER in Paris in that it would ideally provide 15-minute headways and all-day service on commuter rail. A major barrier to commuter rail ridership growth is the limited service provision. Three-quarters of all commuter rail stations typically get less than 24 trains per day, or roughly one train per hour. Frequencies are normally higher during the peak hours and lower off-peak, meaning there are often gaps of two hours or longer between trains in the off-peak. Leisure trips are much less likely to occur when a service requires careful time management to ensure passengers can make it on time to the train, especially given the next train might not arrive for a few hours.

The MBTA Fiscal Management and Control Board recently declared the intentions of upgrading the commuter rail system and increasing frequencies. While this process could potential take decades to complete, it is a step in the right direction for increasing commuter rail capacity and ridership. The Leisure Campaign could be one tool to help incentivize leisure trips on the weekend as service increases on commuter rail.

4.5 Implications of Campaigns

Overall, there was minimal growth in Monthly Pass and Weekend Pass adoption. However, email marketing is a cheap tool that is still able to shift a non-negligible population over to pass products. This will become increasingly important as the MBTA tries to regain ridership after the pandemic. It is also a useful tool at advertising new fare products that might not be widely known to passengers (such as the Flex Pass or a variation of it).

There are also implications under an AFC 2.0 system. The new fare collection system for the MBTA, labeled “AFC 2.0,” is a collection of projects and upgrades on the MBTA system with the aim of modernizing the fare collection and payment system. One component of AFC 2.0 is the introduction of faregates at core commuter rail stations (i.e. North Station and South Station) which should help reduce fare evasion techniques. Another component is fare integration, which will allow mTicket to be used on bus/subway. Questions still arise on what the transfer rules look like (will it be a free transfer? How long between ticket activation and the bus/subway transfer? Etc). However, the benefit of using one fare medium (mTicket) to access the rest of the MBTA system will likely increase the appeal of mTicket. Finally, AFC 2.0 will be an account-based system. This will allow the MBTA to run email marketing campaigns on all users, not just the mTicket subset of commuter rail passengers. Future studies, upon completion of the account-based system, could help the agency determine the efficiency of email marketing campaigns on bus and subway users.

In summation, an email marketing campaign is a powerful and cheap tool to increase pass sales. It could be used to increase new pass sales, even if modestly, with the only effort involving crafting the email and determining the targeted user groups. With uncertainty around how much people will be traveling as travel restrictions are lifted, these email marketing campaigns could have significant effects on nudging users back to passes. However, it should be cautioned not to overdo the email campaigns. Excessive email marketing campaigns can turn into negative perceptions of the agency by those receiving the emails, viewing it as “spam.” Therefore, email campaigns should be targeted and infrequently sent to the same users (avoid repeat deliveries over a short period when possible).

Chapter 5: Involving Employers in Transit Fare Products

A key influence in the employee commute mode decision-making process is the employer. While often ignored or viewed as a given, the impact of employer transportation benefits on the choices employees make is significant. In the U.S., it was estimated that around 76% of firms owned and/or leased parking spaces for their employees in 1997 (Shoup and Breinholt, 1997). Of these, over 97% offered it for free to their employees. The cost of constructing a parking space is around \$21,500 (for a parking structure) not including the land value. Not included in that cost estimate is the opportunity cost of having another usable activity space instead developed on the parking spaces. Despite these high costs, employers have long offered free or subsidized parking to employees as benefits. This subsidy masks the true cost of driving and encourages employees to drive to work. Shoup and Breinholt estimated that 95% of commuters who drove to work were offered free parking.

Therefore, the transportation benefits package that employers provide has real consequences on transit ridership. There are many different frames for viewing transportation benefits. Transportation Demand Management (TDM) policies often explore a variety of policies with the intention of decreasing solo driving. Transit agencies prefer when a decrease in parking results in a similar increase in transit ridership, but that is not always the case as many people turn to walking, cycling, or carpooling, among other modes. Additionally, different governing bodies have different regulatory oversight on TDM policies. For example, municipalities may pass TDM ordinances, which require that employers (often targeting just the largest) enact TDM policies aimed to reduce solo driving. State governments may also pass similar TDM measures, such as the parking cash-out policies in California (California Air Resource Board, 2009) and Rhode Island (Employer Programs, n.d.). Transit agencies, however, do not have regulatory authority to mandate TDM policies. Instead, their best tool is to create employer fare products that increase transit access to employees at a reduced rate.

Some transit agencies have already introduced products for employers. The ORCA card in Seattle has two employer products: the ORCA Business Choice and ORCA Business Passport. Business Choice is similar to the corporate program that other agencies offer where employers allow employees to purchase passes or load their pre-paid ORCA card for pre-tax payroll deductions. Employers are not required to subsidize the transit passes or tickets but are able to if they choose to do so. The ORCA Business Passport attempts to integrate TDM ideas into the corporate program by requiring a universal, zero marginal cost pass. The Business Passport is universal in the sense that all employees at a company are required to be offered the transit benefit. It is zero marginal cost since each additional transit trip an employee takes does not add costs. In the Business Passport product, the employer can either fully subsidize transit for their employees (making it free for all employees) or they can charge the employees up to 50% of the cost of the pass. The product is charged annually, and the cost varies by the location of the employer (and based on survey results of transit ridership estimates) that roughly equates to the “pay-per-use value” for each employer in the program.

Many transit agencies provide corporate program benefits similar to the Business Choice product, while very few offer products similar to the Business Passport. Valley Metro, in Phoenix, Arizona, offers a fare-capping pay-as-you-go Employee Platinum Pass for employers. The Platinum Pass is a

pass offered by employers to employees that tracks the usage of each account-based pass and is capped at the cost of a monthly 31-day pass. Employers can decide how they charge or subsidize the transit trips by employees. Additionally, there is no universal requirement on the Platinum Pass, meaning only employees who are interested in using transit are likely to have the pass.

The MBTA has an established corporate program constituting 40% of commuter rail and 35% of bus and subway fares in Fiscal Year 2019. Historically, the only corporate product available to employers was the Corporate Program (renamed “Perq” around the end of 2018, both terms are used interchangeably in this thesis) which allows employers to purchase pass products through the MBTA via pre-tax payroll deductions (more on this in Section 5.1). In 2016, the MBTA piloted a new corporate product, called the “Mobility Pass,” with the Massachusetts Institute of Technology (MIT). The Mobility Pass was designed as a universal, zero marginal cost pass for employees. MIT embedded CharlieCards (the bus and subway smart card for the MBTA) into all employee IDs and offered 100% subsidized bus and subway trips. The Mobility Pass is designed so that MIT pays the MBTA on a per-trip basis, similar to the Platinum Pass at Valley Metro. However, the difference is that the Mobility Pass is available to all employees and MIT fully subsidizes the trips. After analyzing the results of the MIT pilot, the MBTA has considered expanding the Mobility Pass to all employers in Perq, but first wanted to understand the ridership and revenue implications.

This chapter analyzes the Mobility Pass at MIT, examines the ridership and revenue implications of expanding the Mobility Pass to Perq employers, describes the impacts COVID-19 had on the Perq Program, and estimates how a Mobility Pass can help bring ridership back to the MBTA as travel restrictions are lifted and employees return to commuting to their work sites. First, to understand the landscape, Section 5.1 gives an overview of the Perq Program prior to the COVID-19 pandemic. Section 5.2 then introduces the Mobility Pass as a new product and Section 5.3 analyzes the results of the MIT Mobility Pass Pilot. In May 2019, an Employer Survey was distributed to all Perq employers to get a better understanding of the transportation benefits offered at companies. This survey and its results are discussed in Section 5.4 and the results are used in subsequent sections. Section 5.5 analyzes the impacts pre-pandemic on expanding the Mobility Pass to all Perq employers and discusses the methodologies used in predicting ridership growth. The sections mentioned all use an analysis period before the COVID-19 pandemic, which upended the Perq program. The last sections discuss the Mobility Pass in regards to the COVID-19 pandemic, beginning with an overview of the impacts Perq experienced during the pandemic in Section 5.6. Section 5.7 then explores the use of the Mobility Pass as a tool to increase the recovery rate on transit as commuting returns post-pandemic. Finally, Section 5.8 summarizes the analysis and frames the potential of the Mobility Pass or a similar fare product under AFC 2.0, the “next-generation” fare collection system currently being implemented by the MBTA.

5.1 Perq Program Overview

Before analyzing the Perq Program and Mobility Pass, it is important to give an overview of the program in the MBTA. This section will cover an overview of the Perq Program, beginning with a history of corporate programs in the United States and within the MBTA specifically. The second subsection (5.1.2) discusses the financial benefits of a corporate program and the federal tax structure associated with it. Following that subsection is a discussion on corporate third party payroll/fringe benefit administrators, such as WageWorks and Edenred, and their relation to the Perq Program in Boston. The role of third party administrators is an important one to highlight and will be discussed in subsequent sections. The last two subsections show recent trends (pre-

pandemic) in the Perq Program (5.1.4) and a profile of employer sizes and product purchases (5.1.55.1.4).

5.1.1 A Brief History of Corporate Programs

The MBTA was one of the early adopters of a corporate program, beginning in 1974 with two thousand employees from John Hancock Mutual Life Insurance Company purchasing MBTA passes through payroll deductions. The program quickly expanded to the City of Boston and other employers in the Greater Boston area. During the 1980's, there was a constant push to market the employer pass program. On top of that, as part of the 1970 Clean Air Act, Massachusetts required large employers to reduce their single occupancy vehicle trips. Employers were deemed compliant if they enrolled in the Corporate Program, further incentivizing adoption. These efforts led to a doubling of the number of employers in the MBTA Corporate Program (Kamfonik, 2013). As previously mentioned, the legacy of the MBTA Corporate Program led to 35% of bus and subway fare revenue and 40% of commuter rail fare revenue coming from the Corporate Program in Fiscal Year 2019.

Part of the attraction to a corporate program are the pre-tax payroll deductions, which allows employers to deduct the cost of a transit pass from an employee paycheck prior to income taxes being calculated and applied. That system was not in place until the 1990s. Before 1984, transit passes were tax exempt as transportation benefits from employers (parking benefits were considered a taxable fringe benefit). The 1984 Tax Reform Act flipped the benefits, making parking a tax-exempt transportation fringe benefit as was transit previously, except transit was limited to only \$15/month for the tax-exemption and any cost above that would be fully taxed. In 1992, Congress passed the Energy Policy Act which included transit as a “qualified transportation fringe benefit” and allowed up to \$60/month in pre-tax payroll deductions (parking received \$155/month). Despite the disparity between parking and transit, most monthly transit passes nationwide were \$60 or less per month, making them qualified for the full benefit.

The qualified amount for pre-tax payroll deductions increased yearly for parking and transit (with parking being a larger benefit) until 2016 when parking and transit were matched at \$255/month³. Since then, parking and transit have been increasing at the same rate, reaching \$270/month in 2020. While this amount is much higher than the cost of a LinkPass (\$90/month for unlimited bus and subway trips), all MBTA commuter rail Monthly Passes above Zone 3 cost more than \$270/month. This means employees can get up to \$270/month in pre-tax payroll deductions but no more.

5.1.2 Pre-tax Payroll Deductions and IRS Benefits

How do pre-tax payroll deductions work? First, an employer has to be enrolled in a transit agency corporate pass program (or hire a third-party administrator that offers transit benefits). All employees at the company are now eligible for transportation pre-tax payroll deductions. If an employee at the company purchases a monthly transit pass through a corporate program for \$100/month and they make \$3,000 per month in salary, the employee would take \$100 off their salary before applying federal income tax. Let's assume the net federal and state income tax rate is 30% for the employee. If the employee were to purchase a monthly pass outside of the corporate program, they would earn \$3,000 with a 30% tax and spend \$100 on a transit pass. This would result

³ Pre-tax transit and parking benefits matched each other a few times prior to 2016, such as in 2010, 2011, and 2013, but reverted back to the previous disparity in subsequent years. The requirement to match transit and parking was made permanent in 2016.

in a net income of \$2,000 $[(1 - 0.3) * \$3000 - \$100 = \$2000]$. However, if they purchase the monthly pass through the corporate program, they would take \$100 off their income before applying the 30% tax. This would yield a net income of \$2,030 $[(1-0.3) * (\$3000 - \$100) = \$2030]$. That is equivalent to saving 30% on the cost of a transit pass $[(2030 - 2000) / 100]$. Since the marginal tax rates vary based on income levels, the employee savings through pre-tax payroll deductions are variable. However, typical savings⁴ generally range from 25-35% on transit passes through the pre-tax payroll deductions for the vast majority of transit users.

5.1.3 Third-Party Administrators

Since the tax code adjustment in the 1990s, a market was created for what are called “third-party administrators” to assist companies in managing their payroll processes and tax benefits. The two largest third-party administrators in Greater Boston are WageWorks and Edenred. These administrators manage the transportation fringe benefits for other companies, often for a price-per-head (flat rate for each employee at the client company). Third-party administrators typically cover all types of payroll pre-tax benefits, the most common being for healthcare. In many U.S. cities, these third-party administrators are the largest source of corporate program revenue for transit agencies, as they bring employers into the corporate program.

While third-party administrators can help enroll employers into the Perq Program, they appear in the MBTA Perq portal as one employer. This makes it difficult for the MBTA to understand the employer characteristics or communicate with employers when changes occur to the Perq Program. However, the MBTA hired Edenred to manage their web-based Perq portal since the early 2010s. Because of this relationship, Edenred has been cooperative with distributing employer surveys and sharing new information from Perq with its employers. However, neither Edenred nor WageWorks share information on the number or size of employers in their network (more on this in Subsection 5.1.5).

5.1.4 Perq Program Trends (Pre-Pandemic)

The Perq Program (previously Corporate Program) has consistently had over 1,300 employers enrolled in the program leading up to the pandemic. From January 2017 to December 2018, the Perq program had a slight decline in the number of employers ordering from Perq (see Figure 5-1). At the end of October 2018, the Corporate Program was rebranded as Perq “in an effort to modernize the image of the T’s employer pass program and better communicate its ‘perks’” (MBTA, 2018). The rebranding was followed by increased marketing on subway platforms and bus interiors. Since November 2018, the number of employers ordering products in Perq increased from 1,331 to 1,518 by February 2020, just before the pandemic.

⁴ Note that the “savings” are in terms of lower taxes applied to income rather than a cheaper transit pass.

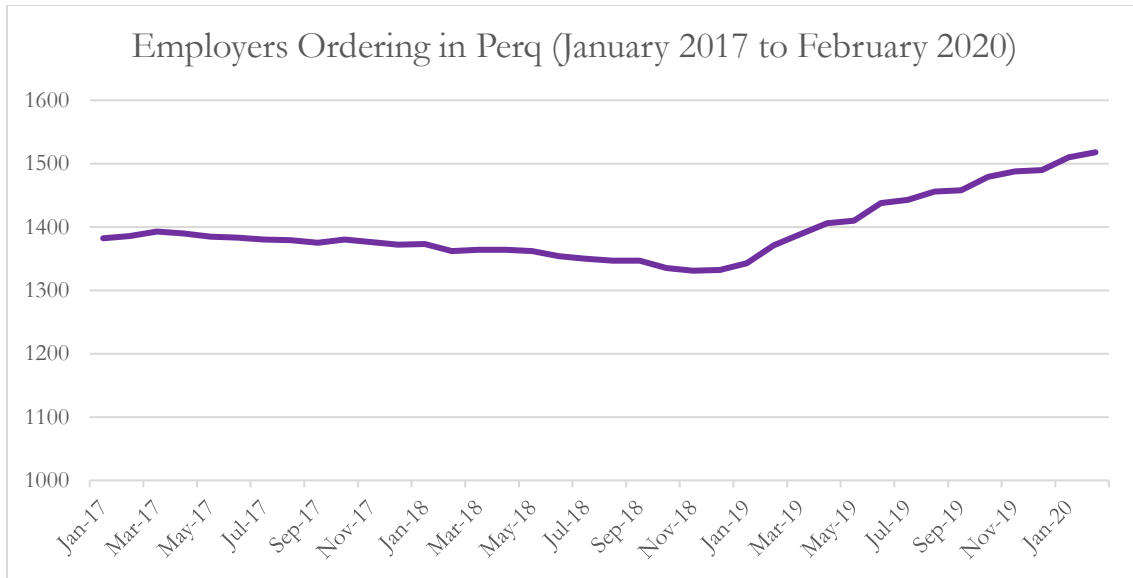


Figure 5-1: Number of employers that ordered a product in Perq (January 2017 to February 2020)

However, the increase in employers in Perq did not correlate to a significant increase in revenue. Between November 2018 and February 2020, the number of employers ordering products in Perq increased by 14%. The number of cards ordered between that same interval increased by 3% for commuter rail and 1% for LinkPasses and Local Bus passes (see Figure 5-2). Revenue saw a larger increase, of 8% for commuter rail and 7% for LinkPass/Local Bus passes, however that is because of the fare increase in July 2019. The likely explanation for this increase in employers but not revenue or cards is that most of the new employers who joined Perq between November 2018 and February 2020 were small companies.

The change in passes ordered and revenue from pass orders from January 2017 to February 2020 can be seen in Figure 5-2. Note that there was a fare increase in July 2019. The fare increase led to increased revenue with minimal changes to pass orders. This is expected, as Stuntz finds that corporate programs are more inelastic towards fare increases than the general transit ridership population (Stuntz, 2018). In fact, there was a 1-3% year-over-year increase each month for all pass orders from 2017 to 2020, despite a fare increase in July 2019. Corporate programs tend to have lower elasticities for multiple reasons. First, they are subsidized to some extent. All Perq employees are offered the pre-tax payroll deduction, which is similar to a 25-35% discount on the monthly pass. Some employers subsidize on top of the pre-tax payroll deduction, giving an even higher discount to those employees. A lower pass price means the fare increase is not as burdensome to Perq users. Additionally, Perq offers auto-renewal, which allow employees to automatically be given a new pass each month. This is similar to an opt-in system, where the employee has to take initiative to opt out of a new monthly pass.

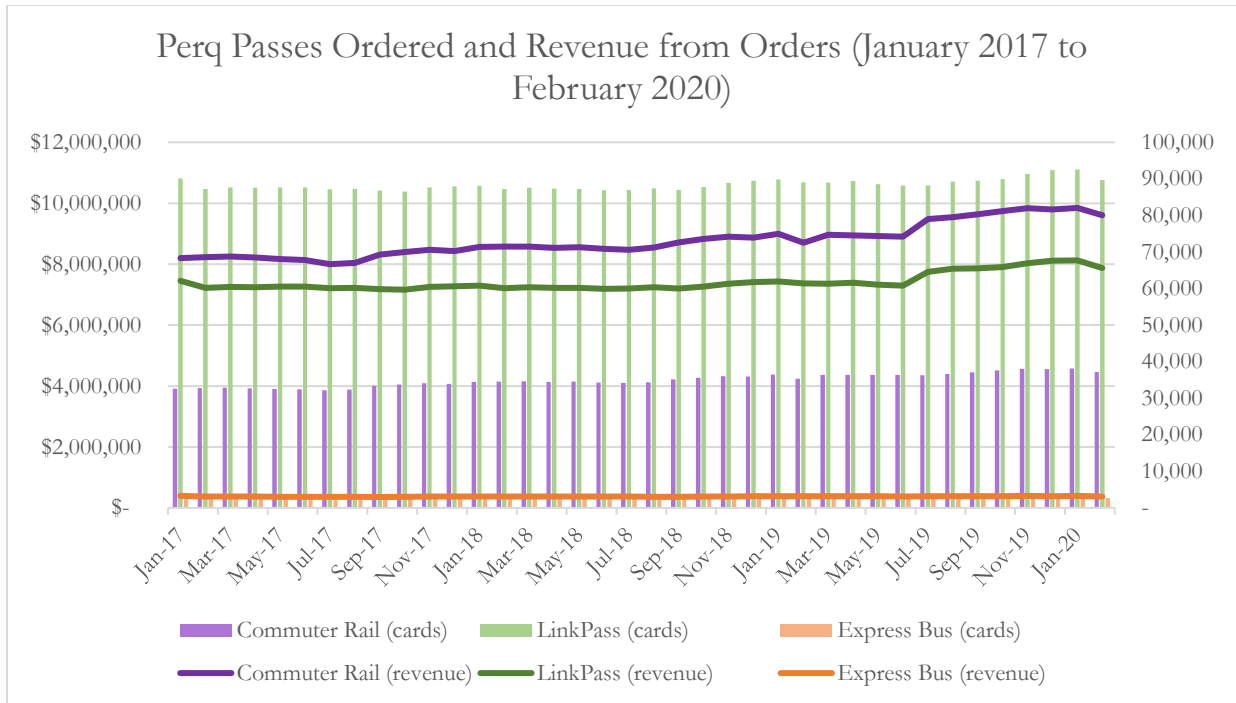


Figure 5-2: Perq passes ordered and revenue from orders by product type (January 2017 to February 2020)

The average monthly revenue for 2019 was \$17.3 Million⁵, of which 98% came from commuter rail and ferry (54%) and LinkPasses and Local Bus passes (44%). The other 2% was from Express Bus passes. Similarly, 98% of pass orders come from commuter rail and ferry (28.5%) and bus and subway (69.4%). Since LinkPasses and Local Bus passes are substantially cheaper than commuter rail passes, they constitute a higher share of monthly passes but contribute to less revenue. While this analysis primarily focuses on the bus and subway ridership, the Mobility Pass is capable of functioning on commuter rail and ferry as well.

5.1.5 Company Characteristics:

The Mobility Pass analysis is conducted over a six-month period between November 2018 and April 2019. This corresponds with the six months preceding the May 2019 Employer Survey (more in Section 5.4). All the data presented is by company and averaged over those six months. The analysis focuses on LinkPasses and Local Bus passes, combined together and called ‘cards’. The Mobility Pass originally only included local bus and subway trips, so only the LinkPass and Local Bus passes were considered. There are 106 (7.3%) companies that did not order any LinkPasses or Local Bus passes and are not included in the analysis (these companies only ordered Commuter Rail, Ferry, or Express Bus passes).

Figure 5-3 shows the cumulative distribution of the number of cards active per company. As shown in the figure, 50% of companies have roughly 7.5 cards or less active per month, 75% have less than 20.5 active cards per month, and 90% have under 53.5 cards active per month. Figure 5-4 looks at the total monthly revenue generated from LinkPasses and Local Bus passes by companies. It shows that the bottom 90% of companies account for a little over \$1 Million out of the roughly \$7.5 Million monthly total. This means the top 10% largest companies in the Corporate Program

⁵ This does not include the existing MIT Mobility Pass Program. All values exclude MIT’s Mobility Pass.

contribute over \$6 Million in LinkPass and Local Bus pass sales. The bottom 50% only contribute about \$160,000 and the bottom 75% contribute a little over \$500,000.

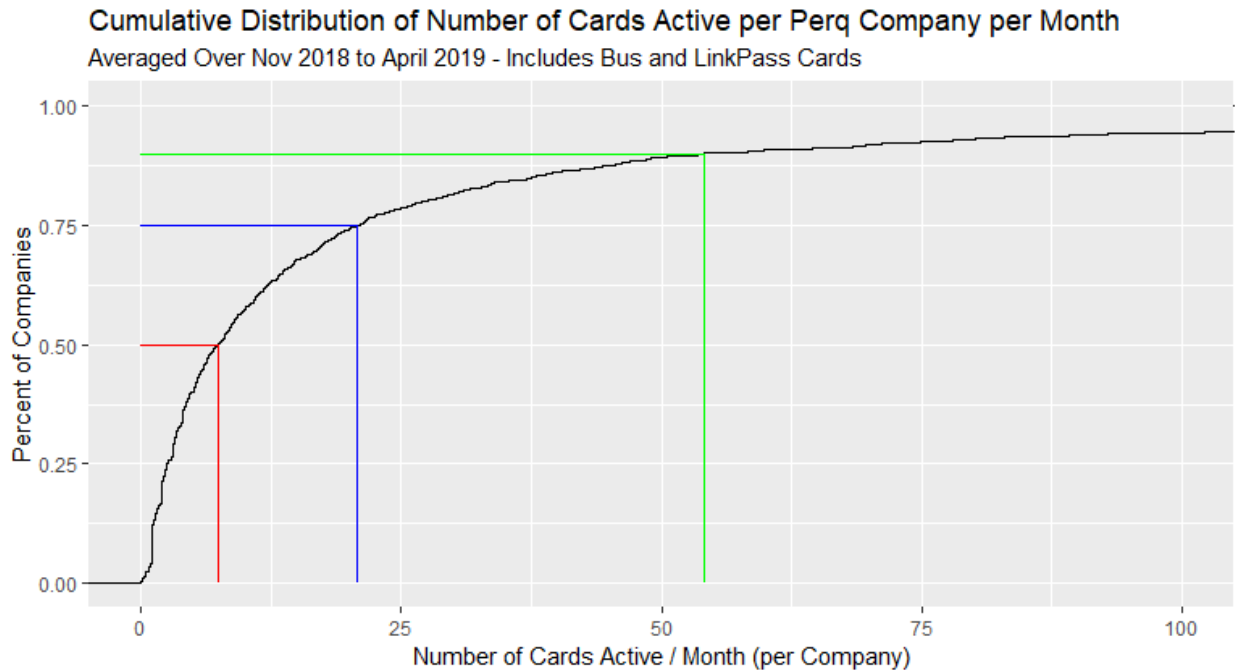


Figure 5-3: Cumulative distribution function of number of active cards per company

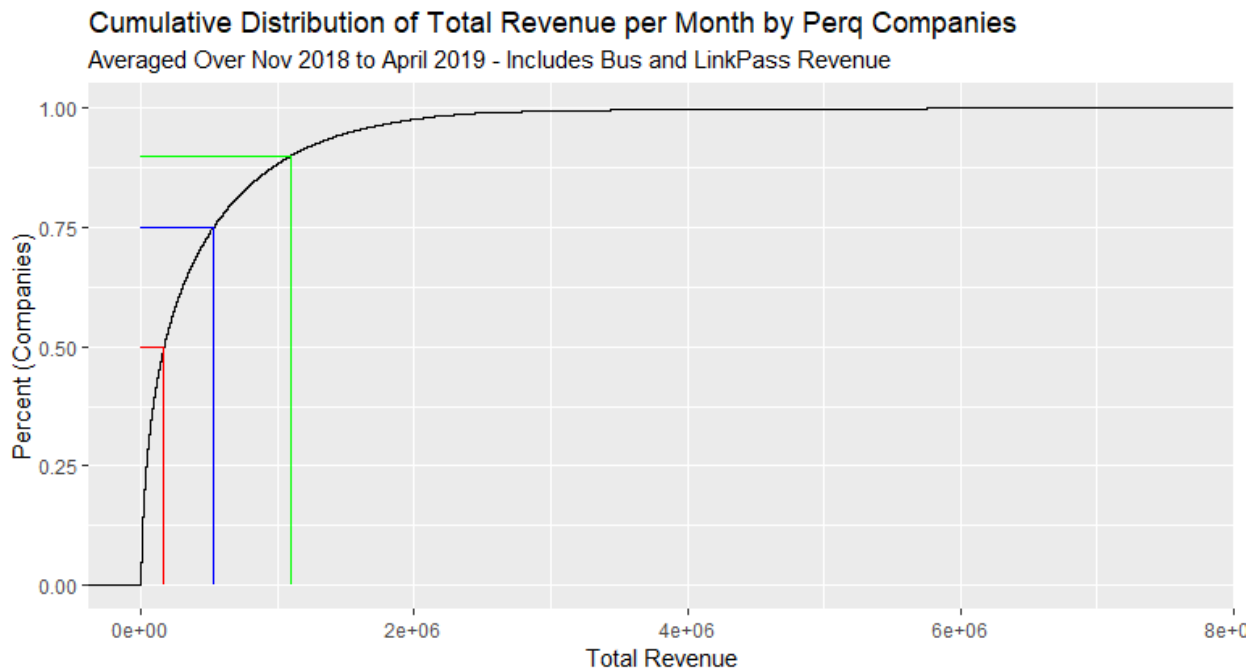


Figure 5-4: Cumulative distribution function of total revenue generated by companies.

However, Figure 5-3 and Figure 5-4 include third party administrators (WageWorks and Edenred), which are a conglomeration of many companies (of all sizes). Together, WageWorks and Edenred account for almost \$2.5 Million of LinkPass and Local Bus pass sales. This is 33% of the overall

revenue generated from LinkPass and Local Bus pass sales. Since these two companies are not single employers but represent a diverse group of other employers, they are excluded from the disaggregate analysis. The disaggregate analysis is later scaled up to the full employer distribution, assuming companies within the third-party administrators are sized similarly to the rest of Perq. The majority of the analysis is based on companies that responded to the Corporate Survey (see Section 5.4), to which there is data on current subsidy levels and total number of employees.

Companies were grouped by the average number of active passes per month, categorized as either under 10 cards (< 10), between 10 and 25 cards (10 – 25), between 25 and 50 cards (25 – 50), between 50 and 100 cards (50 – 100), between 100 and 1000 cards (100 – 1000), and over 1000 cards (Over 1000). A reminder that the term “cards” refers to any monthly pass in this analysis. Figure 5-5 shows shares of companies within each category as well as the share of total LinkPass and Local Bus pass revenue generated by each group. While companies that average over 50 cards per month only account for 10.4% of all companies, they account for 85.9% of the total revenue. This makes sense since their card orders are so large and follows with the cumulative distribution function graphs shown above. If you exclude WageWorks and Edenred (which account for companies of all sizes), the percent of companies that average over 50 cards per month is 10.3% but they only account for 78.9% of the revenue (see Figure 5-6). Regardless, since these companies account for the majority of the LinkPass and Local Bus revenue, this analysis will focus on companies that average at least 50 active cards per month.

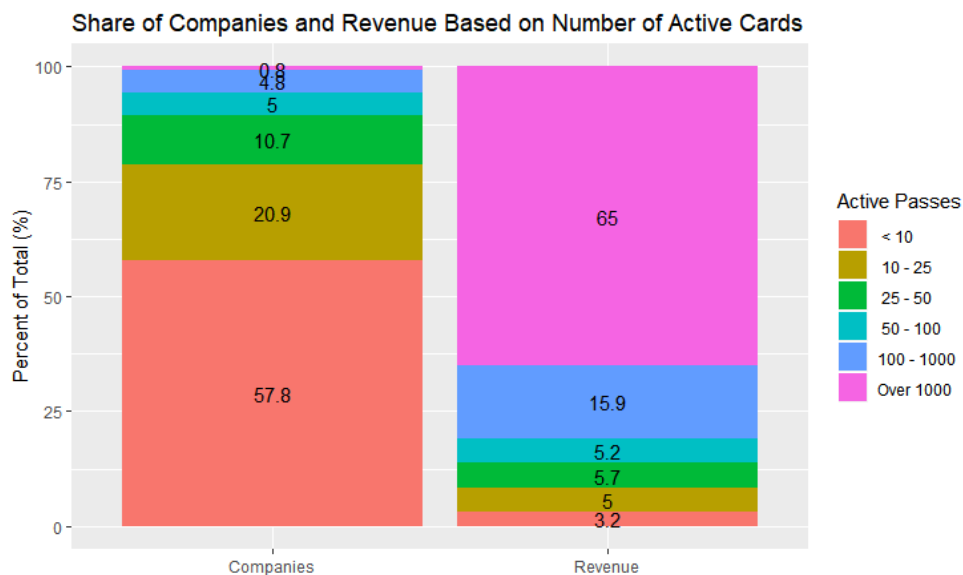


Figure 5-5: Share of all companies and revenue based on number of active cards.

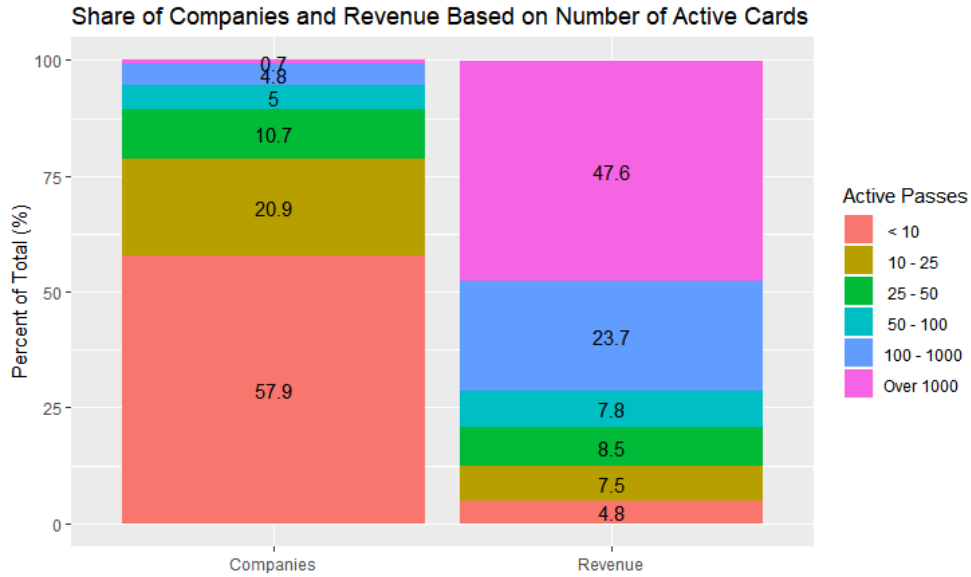


Figure 5-6: Share of companies and revenue based on number of active cards (excluding 3rd party administrators)

5.2 Introduction to the Mobility Pass

In the summer of 2016, the Massachusetts Institute of Technology (MIT), in a partnership with the MBTA, piloted the “Mobility Pass” (more on this pilot in Section 5.3 and Appendix C.). The Mobility Pass offered 100% subsidized bus and subway trips on the MBTA to all employees. Without the Mobility Pass, MIT would have to purchase a full monthly LinkPass for all employees in order to offer 100% free transit. This would cost \$90 per employee or about \$900,000 per month for MIT’s 10,000 plus employees. Instead, the Mobility Pass offers the convenience of a fully subsidized transit pass to all employees and MIT only pays the MBTA on a per-use basis for all trips taken on these passes.

There are three key features of the Mobility Pass Pilot: universality, zero marginal cost, and fully subsidized. Universality means that every employee is offered the Mobility Pass, rather than only those who “opt-in.” Many employers allow employees to take either a parking subsidy or a transit subsidy, but not both. This discourages multi-modality between driving and transit, as employees can either receive the transit subsidy or parking subsidy but cannot benefit from both over the same month. The universality condition offers the transit benefit to all employees, whether they take transit every day, sometimes, or never. The second feature, zero marginal cost to employees, means each additional trip taken by employees does not cost the employee anything more. Full subsidization of transit is not required for the zero marginal cost condition as employers might charge employees a “transportation fee” as a flat rate for all employees. The only condition for the second component is that an employee taking 50 trips in a month is charged the same as one taking 2 trips, whether they are charged, say, \$20 per month or nothing. This condition maintains the benefits of a pass product which avoids adding additional costs to heavy users. Finally, the full subsidization feature means the employer (MIT) covers the full cost of bus and subway trips for employees. While the MIT pilot included all of the three features of the Mobility Pass, not all three are required in the implementation of the Mobility Pass (more on this in Section 5.5).

5.3 MIT Mobility Pass Pilot

In 2016, MIT and the MBTA conducted a pilot of the Mobility Pass, where MIT offered universal, fully subsidized transit to its employees and was charged by the MBTA on a per-use basis for all bus and subway trips taken by its employees. In addition to the Mobility Pass, MIT restructured their transportation benefits for all employees in what they labeled “AccessMIT.” Other changes to the transportation benefits included a shift from annual parking passes to a daily parking charge⁶, an increase in the commuter rail pass subsidy, a new subsidy for transit station parking, and the addition of an online commuter dashboard. AccessMIT served multiple goals for MIT, from reducing carbon emissions, to improving transportation benefits, to (what might be the most important factor) reducing parking demand on campus in order to demolish deteriorating parking garages and smaller surface lots in order to construct new campus buildings.

5.3.1 AccessMIT Transportation Benefits

Prior to AccessMIT, employees were offered a 50% subsidy on all transit passes and parking passes were annual. AccessMIT provides fully subsidized bus and subway trips (through the Mobility Pass), an increase to a 60% subsidy on commuter rail passes, and a switch from annual to daily parking. The switch from annual to daily parking reflects the interest in providing flexibility for MIT employees. Annual passes are sunk costs that employees would have to make at the beginning of each year. After purchasing an annual parking pass, an employee is more likely to drive to work given they have already paid for full year of parking. A daily parking charge allows employees to drive some days and take transit other days. This increases modal flexibility for employees, especially when paired with fully subsidized bus and subway trips.

5.3.2 Key Takeaways

An in-depth analysis of the MIT Mobility Pass impacts from 2014 to 2020 can be found in Appendix C: and supplemental information on the MIT Mobility Pass from 2014 to 2018 can be found in Rosenfield, 2018. This section discusses key takeaways from those analyses in relation to expanding the Mobility Pass to all employers. Data sources for these analyses are the MIT ID tap information (data is collected for MBTA trips and parking at gated lots), a biennial commuting survey, and supplemental sources, such as permit and pass sales from the MIT Parking and Transportation Office.

Daily parking (calculated as the number of employee-days parked) at MIT decreased from 493,000 to 475,300 in the first year of AccessMIT and saw similar numbers in the 2018-19 academic year, despite an employee growth rate of roughly 2% per year. Linked trips on the Mobility Pass have increased from 1.66 Million to 1.72 Million from 2016 to 2019. When looking at the most recent academic year before MIT moved primarily remote, transit continued to increase in the first half of the 2019-20 academic year and parking also had higher volumes, albeit lower than the year before AccessMIT. At the institute-wide scale using MIT ID tap data, parking had decreased in the first two years then increased in the following two years. Transit, on the other hand, has continued to increase each year since AccessMIT began.

⁶ The daily parking charge was set at \$10 but total annual parking charges were capped at the price of the previous year’s annual parking pass.

Another dataset is the MIT biennial commuter survey. This survey is conducted in the Fall semester on even years, with the most recent one being conducted in 2018 (a survey was skipped in 2020 due to the pandemic). While the survey is optional, it is distributed to all faculty, staff, and students and often gets a response rate above 50%. Based on this survey, employees increased their public transit usage and decreased their drive alone rates. There are two metrics used to estimate the mode of choice by MIT employees: a primary and secondary mode question and a trip diary of the previous week. The primary mode shows a decrease in drive alone rates by MIT staff from 29% to 24.8% and a simultaneous increase in public transportation rates from 44.2% to 49.6% between 2014 and 2018 (see Figure 5-7). The drive alone rate remained the same in 2016 as 2018 but the public transportation rate increased by 1.9 percentage points. The 2018 survey saw a decrease in walking, cycling, and carpooling compared to 2016 and a slight increase in work from home and transportation network company (TNC) or taxi use.

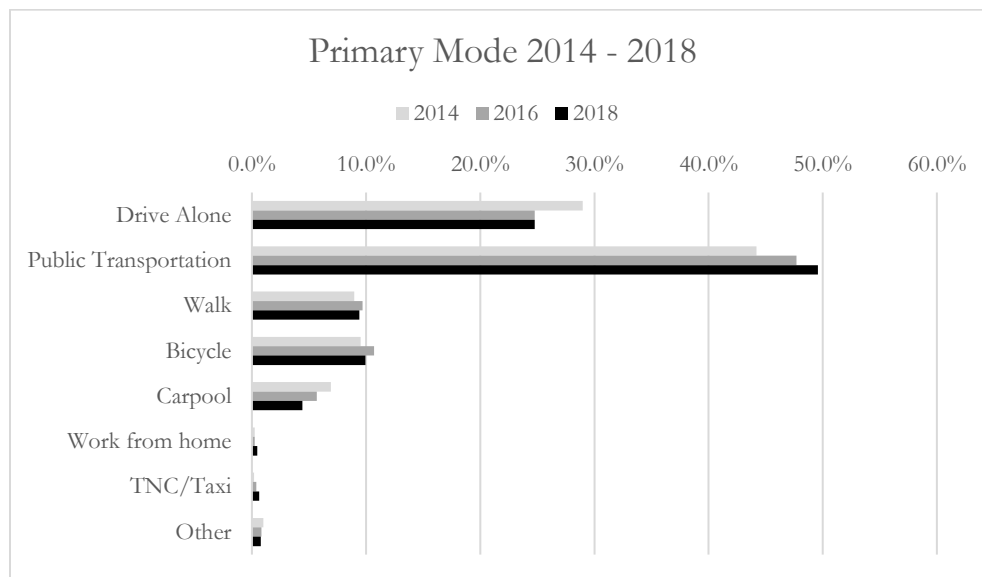


Figure 5-7: Primary Mode Responses from 2014 to 2018

Figure 5-8 shows the percent of commute-days for each mode based on the trip diary. The trip diary covers a full week (Monday to Sunday) and allows respondents to input days they did not work. The percent for each mode was calculated by summing the days a mode was taken to work and divide it by the total number of days a person worked at MIT. The trip diary shows a similar rate for drive alone but a lower rate for public transportation than the primary mode question. While the primary mode question showed almost 50% of employees using public transportation to commute to MIT, the trip diary indicates around 44.2% of employees took public transportation on days they worked. This illustrates the discrepancy in using the primary mode compared to the trip diary. The work-from-home rate is also significantly greater in the trip diary than it is in the primary mode (6.7% in 2018 compared to 0.5% from the primary mode question). Note that this was taken before the global pandemic, when work-from-home was much less common. The difference between the trip diary and primary mode is important to note, as many employees (before COVID-19) would take a day or two to work-from-home each week. It is likely that this flexibility will increase when MIT fully opens campus up again.

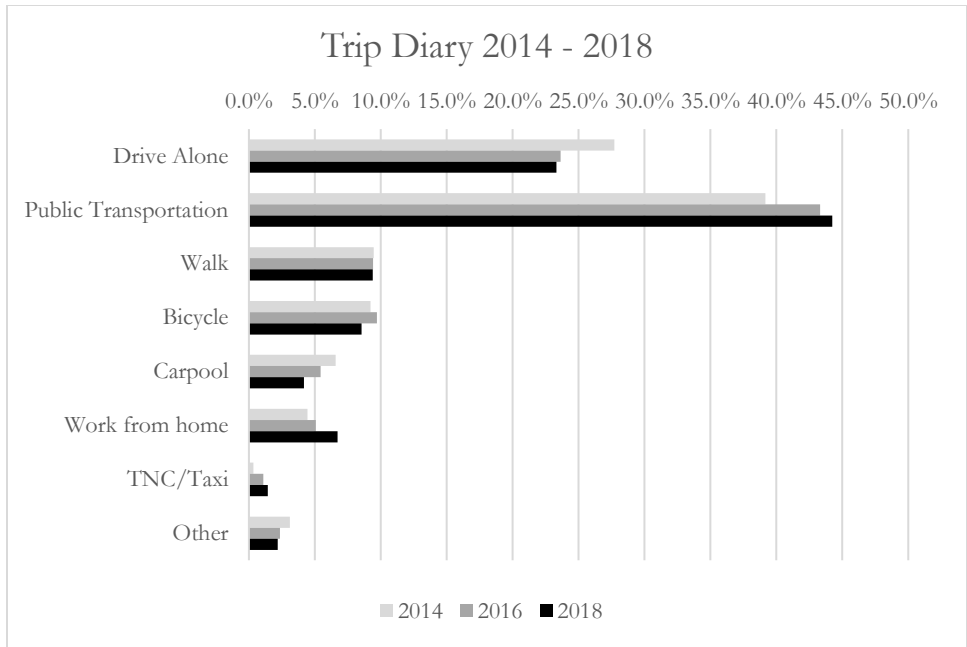


Figure 5-8: Trip diary responses from 2014 to 2018

Another component of AccessMIT was to create competitive transportation benefits for employees to draw and retain top talent. The biennial commuter survey asks respondents how satisfied they are with the transportation benefits offered to them. Figure 5-9 shows the employee satisfaction with the transportation benefits offered at MIT between 2014 and 2018 and Figure 5-10 shows the employee satisfaction with the transportation benefits broken down by their primary mode in 2018. Employees have been pleased with AccessMIT with over 85% of employees either somewhat satisfied or very satisfied with the transportation benefits in 2018. Employee satisfaction increased from 75.9% to 84.6% in the first year of AccessMIT. That increased to 85.6% in 2018. Employees appear to appreciate the flexible benefits offered through AccessMIT, which was a goal for MIT.

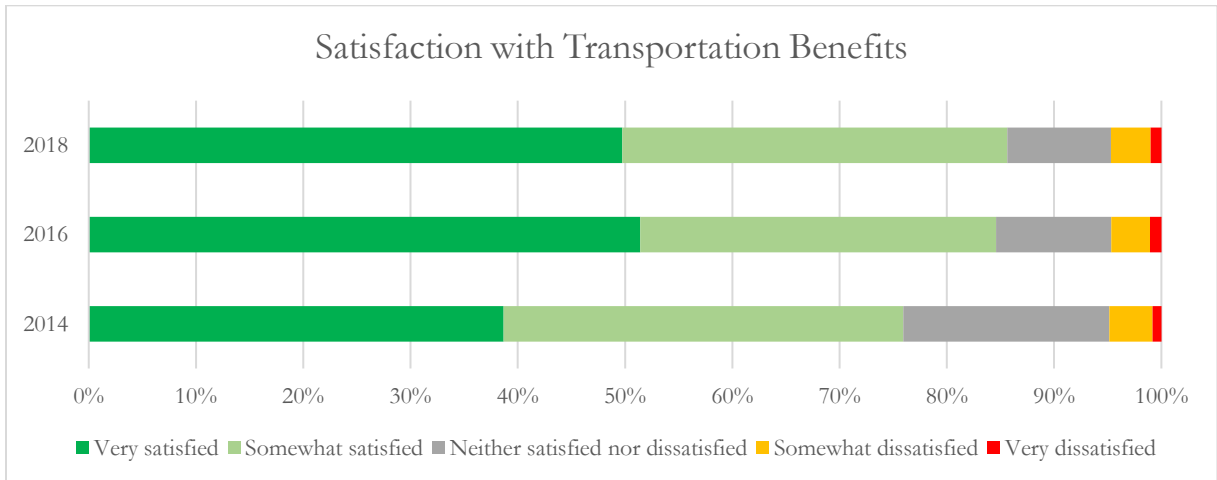


Figure 5-9: Employee satisfaction with the transportation benefits offered at MIT from 2014 to 2018.

Satisfaction with the transportation benefits is highest with employees who indicate public transportation as their primary mode of commuting. Walking and cycling have the next highest satisfaction levels with AccessMIT. This is interesting as there are no direct financial benefits to

employees who walk to MIT. However, it is likely that many employees who walk to campus also take transit and would benefit from the fully subsidized Mobility Pass. It is likely that employees who walk to MIT would also live near transit stations and could benefit from taking transit outside of work. For cyclists, MIT offers a discounted BlueBikes (the local bike share system) membership as well as bike parking facilities around campus. Employees who primarily drive to work show the lowest satisfaction levels with the transportation benefits, although over 70% are still somewhat or very satisfied with the transportation benefits. While the annual pass was replaced with daily parking fees, these are capped at the annual rate to avoid unfairly charging employees who cannot access campus from alternative modes.

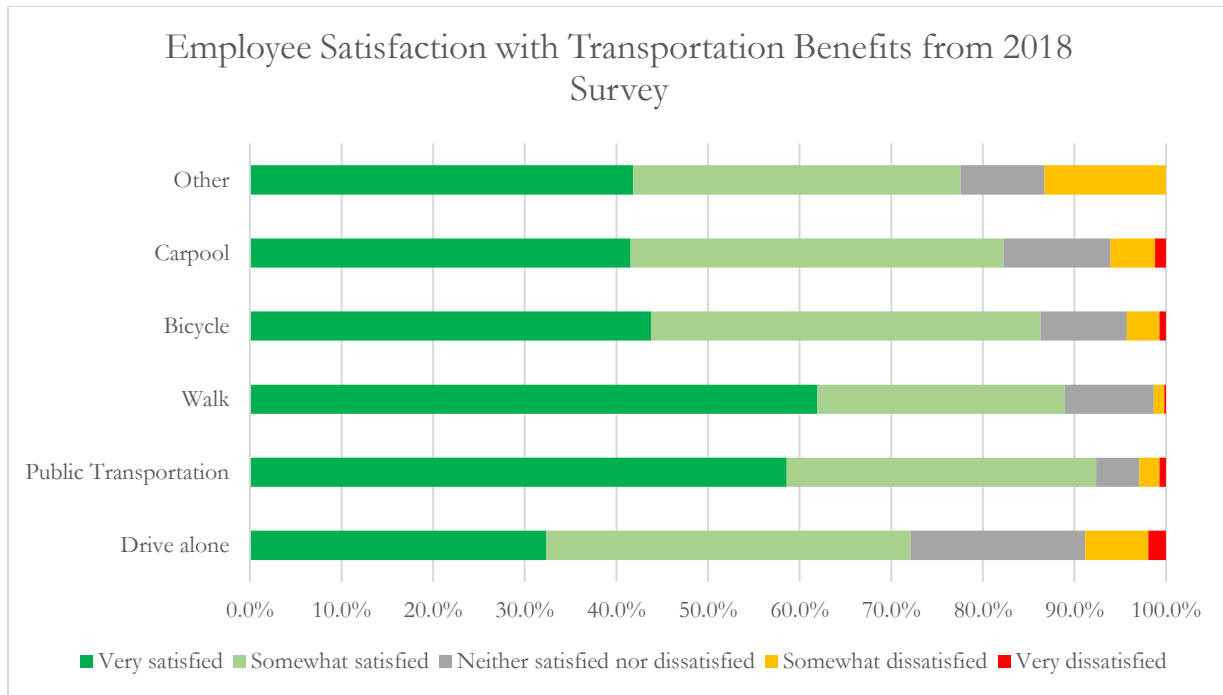


Figure 5-10: Employee satisfaction with the transportation benefits offered at MIT in 2018 by primary mode response

5.3.3 Employee Subgroups

At the institute-wide scale, it appears AccessMIT was able to moderately shift users away from driving and towards transit through daily parking and fully subsidized transit. However, who were the users who switched to transit? Who stopped driving? This section summarizes the travel patterns that emerged from employees who were employed between 2014 and 2018 (“Panel” group), new employees and their trends (“New Employee” group), and employees who take multiple modes to access MIT (“Multi-modal Employee” group). A deeper discussion on each of these groups can be found in Appendix C:.

The “Panel” group consists of employees who were employed and responded to the biennial survey in each year between 2014 and 2018. The biennial survey showed that this panel decreased their drive alone mode share by 1-2 percentage points in both the trip diary and primary mode. The primary mode saw an increase in transit of around 1 percentage point while the trip diary saw very little change. Parking taps decreased in the first year of AccessMIT but increased in the following two years. Transit data, on the other hand, saw a consistent increase in usage. These statistics suggest that AccessMIT had immediate effects on transit and driving (increased transit and decreased driving) but driving returned after a few years. The differences between stated trip diary and revealed

tap data is likely due to the cross-sectional time frame for the survey (one week in October) compared to the method-specific tap data (gated garages for parking and MBTA bus or subway for transit). Employees who take commuter rail and/or the EZ Ride (a shuttle service for Charles River TMA members, of which MIT is one of the largest) or who park in non-gated or off-campus lots are not captured on the tap data. The survey does not account for seasonal variation and revealed modal choices. There are inconsistencies between the datasets, but examining both help paint a picture of how employees are traveling.

Turnover at MIT is roughly 30% every two years, so the impact from new employees is significant. There are two components to the new employee analysis. The first examines new employees every two years (i.e. did not work in 2014 but did in 2016) while the second looks at how new employees change their commuting behavior over time (i.e. the modal trends from those who began working just before 2016 looking at their 2018 data). This distinction is helpful as new employees tend to be younger and have lower paychecks but will usually see increased wages with time.

New employees are known for the 2016 and 2018 surveys. They are defined as employees who were not employed at MIT when the previous commuter survey was released, meaning they have worked at MIT for less than two years. New employees are more likely to indicate public transportation and less likely to indicate driving alone as their primary mode compared to the overall employee average. In 2016, 47.7% of all MIT employees had their primary mode as public transit, whereas this number was 55.8% for new employees. A quarter of all employees indicated driving alone as their primary mode whereas only 12.2% of new employees indicated driving alone as their primary commute mode. Similarly to the primary mode, the trip diary shows a lower drive alone rate and higher transit rate than all employees in each given year (see Figure 5-11) This matches the general understanding that new employees are likely to earn less and, therefore, less likely to own a vehicle and drive to work. Additionally, new employees are more likely to live closer to work than the more experienced counterparts.

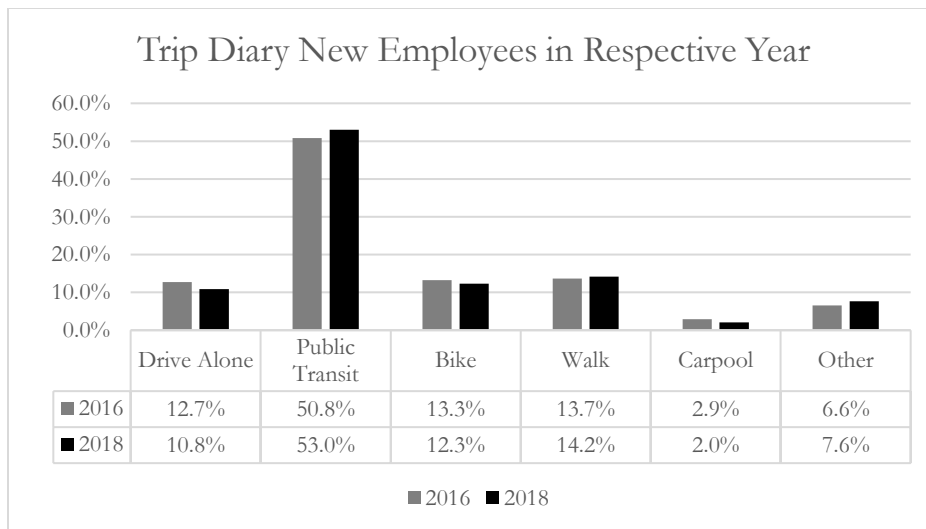


Figure 5-11: Trip diary by new employees in each respective year

New employees tend to see a gradual decrease in public transit usage and an increasing in driving alone the longer they stay at MIT. This is shown by following the modal trends from new employees who began between 2014 and 2016. The drive alone mode share among these employees increased from 12% to 17% (both as a primary mode and in the trip diary). Public transportation rates

dropped by about 1.5 percentage points over the two-year period. Cycling and walking both saw a decrease of about 2 percentage points over the two-year period. This matches the expected trend. However, it is important to note that the shift away from transit and towards driving is slow and not immediate.

As is consistent with the trip diary, the parking data for employees who started between 2014 and 2016 and who were still working in 2018 showed an increase in average days parked per week (0.41 to 0.57). However, the trip diary estimated a decrease in days per week riding transit (2.54 to 2.46) while the transit data showed an increase in transit use from 1.88 days per week to 2.00. Similar to other data trends, the trip diary overestimates the days taking each form of transportation per week (see Appendix C.6).

Table 5-1: Parking and transit data for employees who started at MIT between 2014 and 2016

Avg Days / Week	2016-17	2017-18	2018-19
Transit Data	1.88	1.98	2.00
Transit Trip Diary	2.54	-	2.46
Parking Data	0.41	0.45	0.57
Parking Trip Diary	0.83	-	0.89

It is often assumed that people stick with one mode of transportation when they commute. However, in cities with multiple available modes of transportation, employees have options in how they commute to work. With trip chaining as well, some modes of transportation might be more efficient on some days compared to others. For example, if an employee plans on picking up their child from school after work, they might choose to take transit if the school is near a transit route. On days they aren't picking up their child, they might bike to work instead. This analysis focuses on exploring the multi-modal tendencies of MIT employees. It relies mostly on the trip diary but also uses the MIT ID tap data to add substance and only looks at the 2018-19 academic year (most recent full data available). Based on the trip diary, 27.2% of employees claimed to take more than one mode to campus (not including working from home). The vast majority of these took just two modes, but a few took three or more modes in the trip diary.

Figure 5-12 shows a boxplot of the average weekly days parked and traveled to campus on transit grouped by the most common trip diary response. This grouping was done to better compare the trip diary with the tap data, since the trip diary can better show multi-modal tendencies by employees than the primary mode. As is expected, those who claimed to mostly drive or take transit in the trip diary saw the highest proportion of employees parking or taking transit, respectively. Carpool had the next highest proportion of parkers, likely due to some of them being the driver of the carpool and also potentially to them driving alone some days. Biking and walking had a sizeable transit usage cohort, which suggests they take the T on occasion. Interestingly, the TNC/Taxi users have a relatively high transit usage and minimal parking.

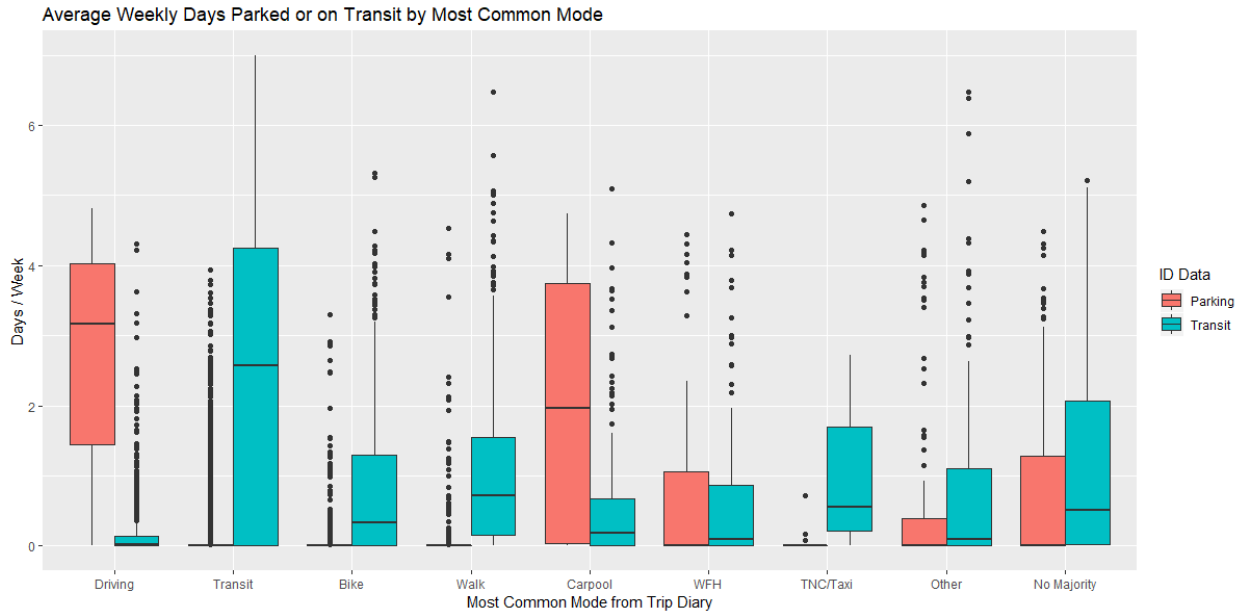


Figure 5-12: Boxplots of parking and transit tap data by the most commonly indicated mode in the trip diary

Table 5-2 shows the average days per week that employees parked and took transit, as well as the average number of licenses and autos per household for MIT employees grouped by the most commonly indicated mode in the trip diary. As anticipated, those who drive or commute in a carpool have the highest average days per week they parked on campus. Those who primarily took transit, walked, took a TNC or taxi, or cycled had the highest average days per week taking transit. In fact, those who primarily walked had an average of 1.06 days taking transit per week. Those who walked also have the lowest number of licenses and vehicles per employee household as well. Employees who primarily took public transit in the trip diary had a higher number of licenses and autos per household than those who biked, walked, or took a TNC/taxi to campus. This could be in part because transit includes a greater reach than biking or walking. For example, many employees who take the MBTA might live in the suburbs and take commuter rail. Many commuter rail riders drive to the stations since the density around stations is low. These commuters still take public transit, but also own vehicles and use them to access transit.

Table 5-2: Average days parking or taking transit to MIT and average licenses and available autos per household by the most commonly indicated mode in the trip diary

Majority TD	Parking	Transit	Licenses	Autos
Drive Alone	2.67	0.16	2.05	2.02
Public Transportation	0.17	2.46	1.81	1.27
Bicycle	0.13	0.81	1.76	0.86
Walk	0.11	1.06	1.46	0.63
Carpool	1.99	0.58	2.20	1.78
Work from home	0.74	0.70	1.91	1.60
TNC/Taxi	0.03	0.85	1.50	0.72
Other	0.67	0.96	1.87	1.54
No Majority	0.72	1.13	1.85	1.37

Between drivers and transit users, there were 8.9% of employees who indicated taking transit and driving to MIT at least one day in the trip diary. Out of the same portion of employees who answered the survey, there were 6.3% who had an average of at least 0.5 days / week on transit or parking on campus. While these two values do not line up nicely, the tap data does not include commuter rail users and employees who park in lots or leased spots off-campus. This could partially explain why the trip diary combination of driving and transit is higher than the actual tap data. Regardless, even among transit and driving, there are a sizable number of employees who switch between transit and driving to campus.

The addition of the Mobility Pass has further enabled employees to utilize multiple transportation modes with free bus and subway trips on top of the daily parking charges. Transit ridership has seen a consistent increase and tends to be highest among new employees. Drive alone decreased in the first year but has increased slightly since. The initial decrease in parking and increase in transit is a result of AccessMIT, while the gradual increase in both in the years following AccessMIT could be due to the increase in the employee population. Nonetheless, the Mobility Pass has been able to increase transit ridership by a substantial amount at MIT.

5.4 Employer Survey

Overall, the MIT Mobility Pass pilot was successful in shifting employees onto transit. Even after the initial shift at the beginning of AccessMIT, transit ridership continued to increase in the following years. Based on this success, the question became how successful would the Mobility Pass be if offered to all employers in Perq? In order to answer that question, more information on the employers in Perq would be needed. Thus, a survey was distributed in May 2019 to all employers in Perq. The survey asked about the transportation benefits offered at the companies, including subsidies, parking availability, shuttle service, and other benefits. It also asked for the number of employees, which is an important metric for knowing how many current non-passholders there are (potential new ridership).

5.4.1 Survey Sampling and Perq Population

The survey was fully completed by 374 companies (26% of active companies in May 2019). Figure 5-13 shows the company size distribution of survey respondents and the overall Perq Program. For the most part, the distribution of survey respondents matches the overall distribution well based on the size of the employer (using active cards as a proxy). Active cards are defined as LinkPasses or Local Bus passes that were active. The other method of comparing the employer sizes are by using the card orders made by employers. However, card orders are often adjusted afterwards and show the anticipated pass usage rather than the true pass usage. Therefore, active cards are used instead.

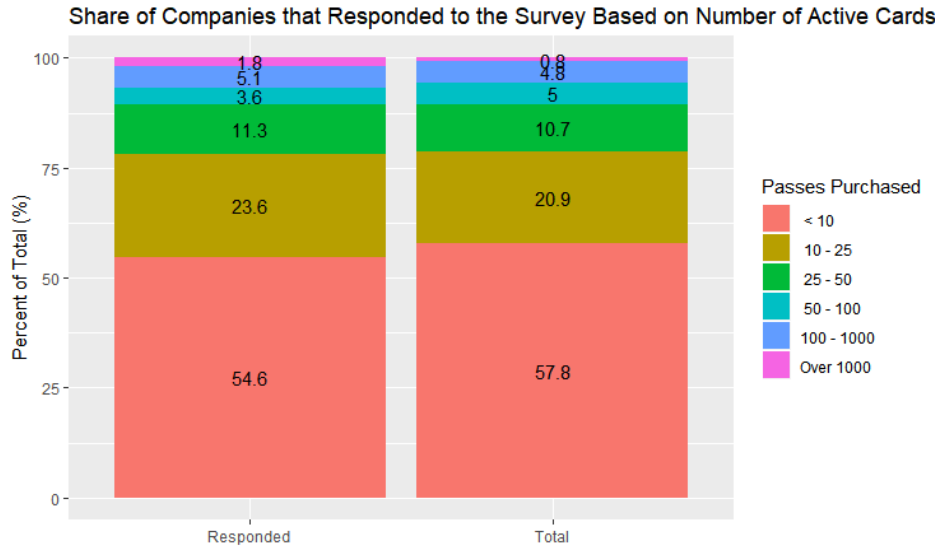


Figure 5-13: Share of companies that responded to the employer survey based on number of active cards

Table 5-3 looks at the location distribution of the survey respondents. The locations of the survey respondents are well distributed around the Greater Boston area and mostly match the overall company distribution. However, Boston was overrepresented in the Survey (77.0% compared to 69.6%) and Cambridge was underrepresented in the survey (11.8% compared to 12.9%). Apart from those three, there was less than a 1-percentage point difference from the survey to the total population. The survey also had a higher representation from employers within I-95, or the inner belt of Greater Boston. This was expected as those employers likely interact with the MBTA more than the employers further from downtown Boston. Additionally, the employers located “out of state” indicate a central office not located in Boston (but a branch office or location is within Greater Boston) so the response rate is anticipated to be lower as they might not be as involved in the Perq Program. Since the survey response was around 26%, not all cities or neighborhoods in the Greater Boston Area were represented in the survey.

Table 5-3: Location distribution of survey respondents

City	Survey		Total	
	Count	Percent	Count	Percent
Out of State	3	0.8%	65	3.8%
Outside I-95	8	2.1%	62	3.6%
Inside I-95	363	97.1%	1598	92.6%
Boston	288	77.0%	1201	69.6%
Brookline	4	1.1%	16	0.9%
Cambridge	44	11.8%	225	13.0%
Newton	4	1.1%	21	1.2%
Quincy	1	0.3%	7	0.4%
Somerville	6	1.6%	25	1.4%
Watertown	7	1.9%	20	1.2%
Woburn	1	0.3%	9	0.5%

5.4.2 Subsidies for Transportation Benefits

One of the reasons for surveying employers was to understand what subsidies they offer for public transit and parking. Additionally, the Mobility Pass is primarily designed for bus and subway trips⁷. Of the 374 companies that answered the survey, 38 did not order LinkPasses or Local Bus passes and were removed from the analysis. The Corporate Survey had a question asking companies if they provide a transit subsidy for LinkPasses or Local Bus Passes, and if so, how much. Of the remaining companies, almost 70% do not offer any subsidy on LinkPasses or Local Bus passes (Figure 5-14). Roughly 14% offer a full subsidy on those passes and 6% offer a subsidy between 40-60% the cost of the pass. There were 21 companies that said they offered a subsidy for LinkPass or Local Bus passes but did not specify the amount they offer.

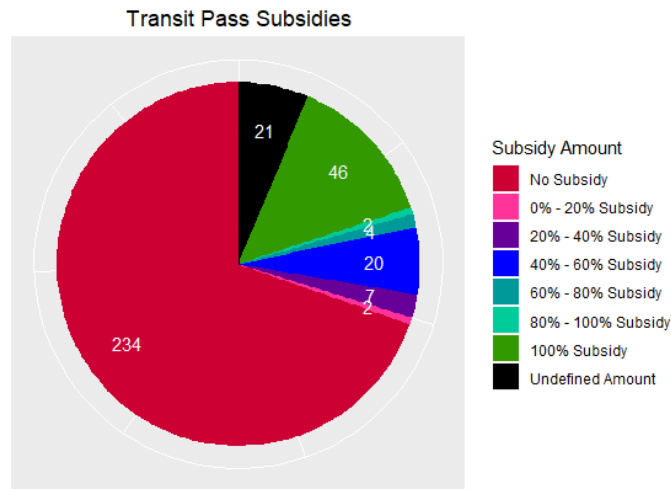


Figure 5-14: LinkPass/Local Bus pass subsidies offered by all survey respondents

Figure 5-15 shows the subsidies offered by the largest companies that responded to the survey (companies with over 50 active cards/month). There are only 35 companies that fit this category, of which 40% offer a LinkPass/Local Bus pass subsidy. However, only 11% offer 100% subsidy. Larger companies are more likely to offer subsidies for transit since they are more likely to have an HR department that can easily administer the subsidy and transit subsidies provide a competitive edge on attracting top talent. Larger companies are also less likely to offer a 100% subsidy since the larger number of employees would drastically increase the cost of providing a subsidy.

⁷ Note that the Mobility Pass can also be applied to commuter rail, but the primary interest of the MBTA was on bus and subway trips.

Transit Pass Subsidies (Companies with Over 50 Active Cards)

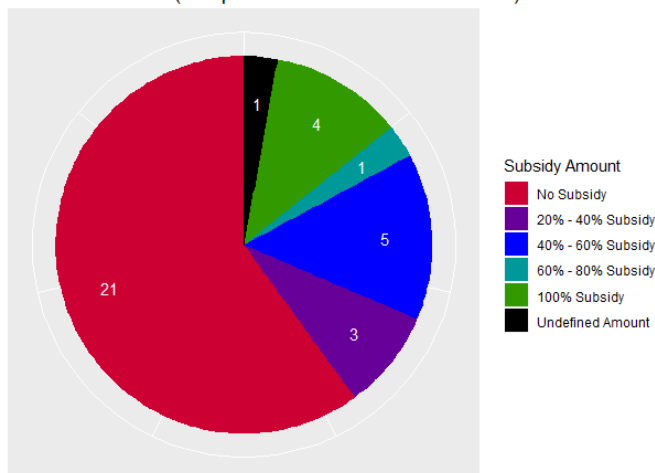


Figure 5-15: LinkPass/Local Bus pass subsidies offered by large employers (> 50 active cards)

The percent of employers offering parking subsidies is comparable to those offering transit subsidies (see Figure 5-16). There are more employers that fully subsidize parking over transit from the survey. Many of these employers have parking available and don't charge employees for accessing the parking spaces. However, many of the employers that offer parking subsidies are much smaller than the employers who offer transit subsidies. If weighted by the number of employees who are offered these subsidies, over 85% of employees are offered a transit subsidy. This is just over 50% for parking subsidies. As previously mentioned, larger employers are more likely to offer transit subsidies as they are often located downtown near rapid transit routes. Conversely, parking becomes significantly more expensive the closer to downtown an employer is located. Thus, it makes sense that larger employers located near downtown are more likely to subsidize transit and less likely to subsidize parking. Nonetheless, a significant portion of employers subsidize parking to some degree, with rough 5% of employees being offered free parking.

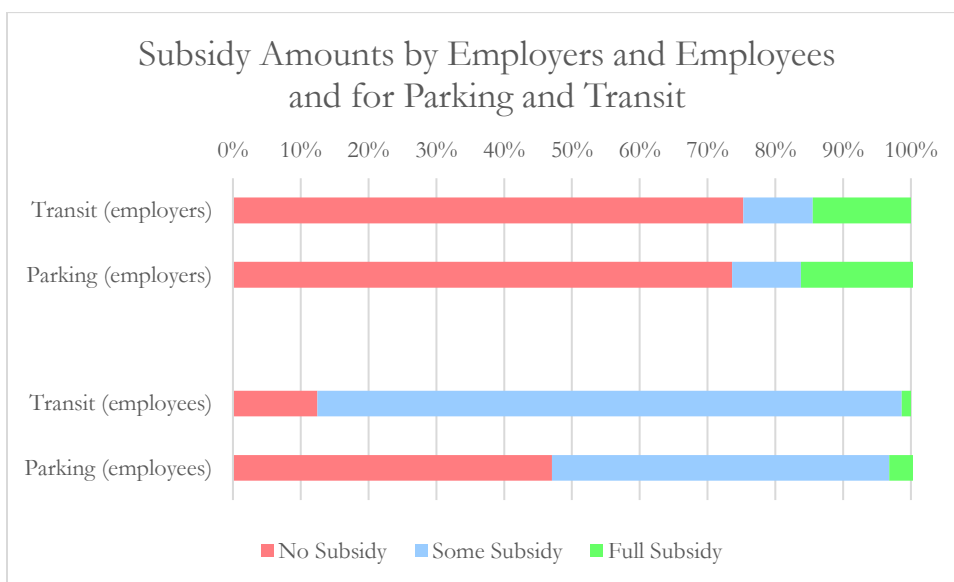


Figure 5-16: Percent of employers offering a subsidy for parking or transit and percent of employees offered a subsidy for parking or transit

A major benefit of the Mobility Pass is offering zero marginal cost transit to commuters who are occasional or infrequent transit users. However, parking can interfere with transit usage if parking is free. At MIT, the marginal cost of parking and transit reversed in the Mobility Program. Employees had to decide whether to buy a subsidized parking or transit pass before the Mobility Pass. Afterwards, all employees received free subsidized transit and had to pay \$10 a day for parking. This discouraged parking and removed the zero marginal cost benefit of parking while giving transit the benefit of zero marginal cost. For other companies, lower ridership growth would be expected from companies that highly subsidize parking. For many companies that own or lease parking spaces, increasing transit ridership would decrease the demand for parking and could save them thousands of dollars on parking spaces. By not having to purchase or build more parking spaces, MIT was saving money with a Mobility Pass despite almost doubling their subsidies for transit.

According to Donald Shoup’s *Parking Cash Out* (Shoup, *Parking Cash Out*, 2005), companies that offer parking subsidies or free parking are likely to have higher driving rates than companies that make the employees pay for parking. Although there is not detailed data on trip modes by employees at each company, most companies gave an estimate of the commuting mode split at their organization. Table 5-4 shows the estimated mode split at all companies who answered the survey weighted by the number of employees at each company and grouped by parking subsidy and employer location. Note that this is an estimate and depends on the accuracy of the survey respondent. Nonetheless, there is a sharp drop in estimated the drive alone mode share from fully subsidized employers compared to those who don’t subsidize. In fact, this is comparable to Shoup’s findings of an average 25-point increase in the drive alone mode share for companies that offer free parking. The reverse is true for the mode share of bus/subway where companies that offer free parking have around 34% of employees taking transit (bus, subway, and commuter rail) while companies that do not offer a parking subsidy have around 50% of employees taking transit. Additionally, the closer the employer is to downtown Boston, the lower driving alone rates and the higher transit rates. This makes sense as transit tends to be more available and traffic congestion is higher in downtown Boston.

Table 5-4: Estimated mode share by employees by parking subsidy and location

Parking Details		Drive Alone	Carpool	Bus/Subway	Commuter Rail	Bicycle	Walk	Other
Free Parking	Central Boston	34.3%	2.9%	42.9%	13.3%	1.9%	3.1%	1.6%
	Cambridge	39.5%	1.5%	38.2%	3.8%	7.7%	5.4%	3.8%
	Other	63.9%	0.5%	23.5%	3.2%	2.1%	3.7%	3.1%
	Total	55.6%	1.0%	28.8%	5.1%	2.8%	3.8%	2.9%
Subsidized Parking	Central Boston	25.6%	7.1%	28.7%	8.3%	3.8%	5.4%	21.1%
	Cambridge	37.8%	1.1%	32.5%	10.6%	8.7%	9.0%	0.3%
	Other	-	-	-	-	-	-	-
	Total	25.7%	7.0%	28.7%	8.4%	3.8%	5.4%	21.0%
No Parking Subsidy	Central Boston	29.0%	3.5%	35.4%	13.1%	6.2%	3.6%	9.1%
	Cambridge	45.4%	1.9%	38.4%	4.2%	2.9%	2.8%	4.4%
	Other	29.9%	0.0%	37.3%	29.7%	1.0%	1.2%	1.0%
	Total	29.4%	3.1%	35.6%	14.4%	5.7%	3.4%	8.3%

5.4.3 Importance of the Employer in Employee Mode Choice

As shown above, the parking subsidies alone can have significant effects on the transit mode share. At a more general level, this highlights the importance of the employer on employee mode choice.

In the fight to reduce carbon emissions in transportation, many advocates turn to mode shift – moving people from driving to another, cleaner mode. The means of accomplishing this feat often involve government regulation to nudge people to a cleaner mode or away from a heavy polluting mode. Alternatively, some advocates turn to education and individual actions of choosing a greener mode. Rarely do advocates, activists, and researchers consider the employer and their transportation benefits or bundles. However, the employer alone can be a primary reason for which mode an employee chooses to take to work.

Employers can impact employee mode choice in a variety of ways. First, the location of the office has significant implications on mode choice. For instance, an office that is located in the outer belt of a city is unlikely to have many public transit connections, meaning most employees will likely drive to work. An office located downtown, or near transit hubs, will have multiple possible ways for employees to access the office (i.e. public transit, driving, walking, cycling, etc.). In fact, Rosenfield (2018) estimated the mode split at fourteen separate offices for Partners Healthcare (now Mass General Brigham) before they relocated all offices to one location at Assembly Row in Somerville, MA (on the Orange Line about two miles north of Boston). Rosenfield then surveyed the mode split for employees at the new office and compared the previous and current mode split by former office location. Offices that were located further away from transit had predominantly drive alone mode shares while those located downtown had a higher transit mode split. Upon relocating to an office just outside of downtown, the employees who were previously in the suburbs saw an increase in transit adoption and the offices located downtown saw a decrease in transit usage and an increase in driving. This highlights the importance of the location of the office on employee mode choice.

However, the location of the office at Assembly Row was not the only change that occurred. Each office had a different parking cost (the transit subsidy was 30% across all offices) ranging from being free (four offices offered free parking) to costing up to \$480/month. Parking at Assembly Row switched to daily parking charges based on salary with the highest wage earners paying the most in parking. Thus, the employees who shifted from transit to driving when Partners concentrated their offices might have shifted due to cheaper parking costs compared to their previous location. The combination of transit access and parking costs are significant factors in shifting employee mode shift. One of the previous offices saw an increase in the driving mode share of 34-percentage points when while another saw a 36-percentage point decrease in the driving mode split with the only differences being the location of the office (and, therefore, proximity to transit) and the cost of parking. Those shifts are significant, as a third of employees changed their travel behavior just from those two factors in two of the fourteen previous offices.

In Table 5-4, the only known difference in the companies are their parking subsidy limits. From that one factor, the transit share shifts from 34% with free parking to 50% without any parking subsidy. That is based on employers who already took the initiative to enroll in the pre-tax payroll benefits for transit and responded to a survey from the MBTA. Driving mode shares are also higher the further from Downtown Boston an employer is located. Conversely, transit ridership is highest with employers located in Boston. Combined together, employers located in Boston that do not offer parking have a driving mode share of 29% while those that offer free parking and are not located in Boston or Cambridge have a drive alone mode share of 64%. That is a difference of 35-percentage points, similar to that of some of the Partners office locations when moving to the Assembly Row location.

While employers, in general, are major factors to employee mode choice, the largest employers have significant influence on regional mode shares. The distribution of employers within Perq (see Figure 5-6) has the largest 10% of employers (those with over 50 transit passes per month) accounting for nearly 80% of revenue. That roughly corresponds to 80% of employee decision-making, attributed to only 10% of companies. Even starker than that, there are only nine employers with over 1000 active cards per month. Those nine employers account for nearly half of all revenue in the bus and subway part of Perq. Thus, any relocation or transportation benefits decisions by those employers impact a significant share of Perq revenue.

This research considers employer locations as fixed. Thus, the only other factor to change are the employee transportation benefits. While the MBTA is unable to control parking subsidies, they are able to offer a transit benefit program, such as the Mobility Pass with MIT. This would only target one of the factors in which employers can influence employee mode choice. However, it might incentivize employers to pair their transportation benefits in a similar way to MIT, who shifted to daily parking costs. This research focuses specifically at the impacts of a Mobility Pass. However, future research should explore the impacts of employer location choices on employee mode shares.

5.5 Expanding the Mobility Pass to Perq

The purpose of this research is to examine the effects of creating a Mobility Pass option that all employers could choose if willing. The structure of the Mobility Pass is based on the current Mobility Pass offered to MIT. The current MIT structure offers a 100% subsidy to all benefits eligible employees at MIT for local bus and subway use. MIT added CharlieCard chips to the IDs of all of these employees to track the usage by these employees. MIT then only pays the MBTA for the pay-per-use cost of the trips taken by all benefits eligible employees. This section estimates the revenue and ridership implications of the Mobility Pass pre-COVID-19. The pandemic caused a significant ridership decline within Perq that would have major implications for this section. However, it is still useful to estimate pre-pandemic predictions as it frames the post-pandemic analysis. More on these topics in Sections 5.6 and 5.7. This section looks at system-wide and company-specific risks and benefits of switching from the current pass structure to a Mobility Pass. Two scenarios were identified to help understand the revenue risk and bound potential growth by companies: worst case and expected ridership growth.

To calculate the expected ridership growth and revenue implications of a Mobility Pass requires knowing how many employees currently use transit, how many use other modes, and how many trips those who use transit take. Determining the number of employees who use transit is mostly straightforward. The employer survey from Section 5.4 asks employers how many employees they had in May 2019. This value is compared to the number of LinkPasses, Local Bus passes, and commuter rail Flash Passes the company ordered for May 2019 through the Perq Program (more on this in Subsection 5.5.1). The number of employees using other modes is partially⁸ estimated using the remainder of the employees who did not order a transit pass. Finally, the amount that employees actually use transit is determined from those who purchased a pass through Perq. Those monthly passes are tracked for their usage and converted to a “use value.” The use value of a monthly pass is the pay-as-you-go equivalent had the user purchased each trip individually rather than from a monthly pass. For example, if a user purchases a \$90 monthly pass and takes 25 subway trips (each

⁸ It is possible that employees who do not purchase a transit pass through their employer still take the MBTA either through external passes or pay-as-you-go tickets. These are taken into consideration in the growth estimate analyses.

\$2.40), they have a use value of \$60 (lower than the cost of the monthly pass). The use value is calculated in Subsection 5.5.2.

There are often slight variations in employer hiring cycles based on the industry. To account for these, this analysis uses data from November 2018 to April 2019, the six months leading up to the employer survey. Active cards are LinkPasses and Local Bus passes that are active per month and are used as the estimated size of the employer. While the number of employees for each employer is known because of the survey, this is not the case for the employers in Perq that did not respond to the survey. To scale the survey results to all Perq employers, the number of active cards is used as a proxy for the size of the organization.

5.5.1 Share of Employment with Transit Passes

Non-passholders are the most important variable for understanding potential ridership growth. Companies that have most of their employees purchasing monthly passes through the Perq Program do not have much potential to increase ridership since most employees would already have zero marginal cost on bus and subway rides. Figure 5-17 illustrates the number of LinkPass/Local Bus, Commuter Rail (including Ferry and Express Bus), and Blank cards ordered as a percent of the total employees at each company. Note that 'LinkPass' includes LinkPasses and Local Bus passes and 'Commuter Rail' includes Commuter Rail, Ferry, Express Bus, and all other monthly passes. Local Bus, Express Bus, and Ferry passes constitute a small share of all passes ordered in Perq.

Blank cards are inactive passes that are sent to large employers that can be activated during the month if an employee needs a pass but did not order one prior. Monthly passes in Perq are ordered by the 15th of the preceding month. In this case, passes ordered after April 15th would not be included in the May monthly pass. If an employee uses a blank card on transit, the card will become active and charge the employer for the monthly pass. Many large employers tend to order more blank cards than they need. For that reason, this analysis considers the participation rate to be the percent of employees who order a transit pass not including blank cards. However, much of this analysis will focus on the non-passholders, or the employees who did not order a transit pass through Perq. These employees are the ones who are most likely to benefit from a Mobility Pass, as they currently do not have a transit pass but would be given one under the Mobility Pass.

Figure 5-17 shows the percent of employees who order a transit pass out of all employees for employers over 1000 active cards. Note that this is less than 2% of all employers who responded to the survey and serves as an example. In general, many employers in Perq tend to have between 40-60% of employees order transit passes. However, each employer is unique with some having much lower shares of employees on transit (such as the employers on the far left).

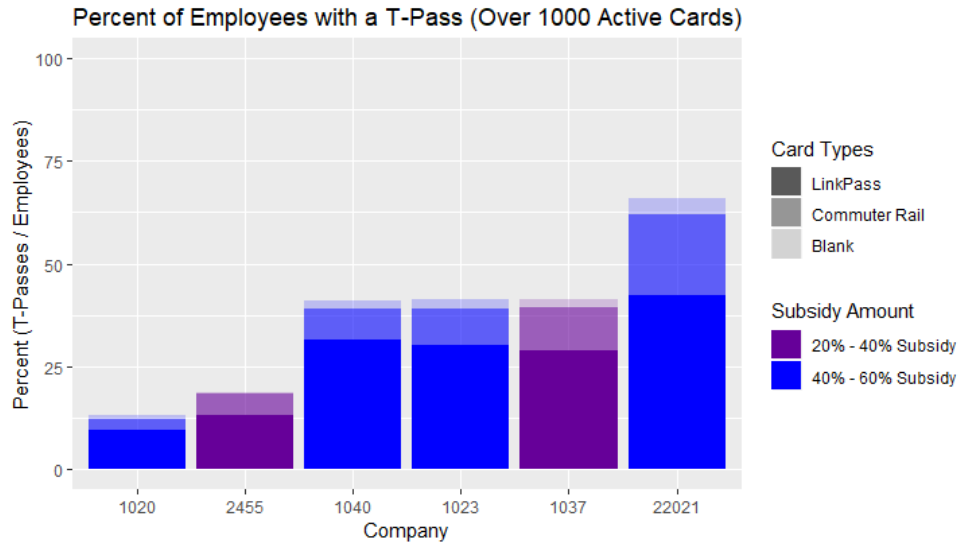


Figure 5-17: Percent of employees with a transit pass for companies with over 1000 active cards

The participation rate (percent of employees purchasing a monthly pass), according to (Kamfonik, 2013), tends to increase with an increase in the subsidy, decrease with company size, and increase the closer companies are to the CBD (defined as Government Center in her research). This tends to be the trend among the Perq employers surveyed (note that Figure 5-17 only shows a subset of all employers who answered the survey). In addition, most companies order between two and three times more LinkPasses than Commuter Rail passes, which reflects the overall trend in the Corporate Pass program as well.

5.5.2 Use Value Distributions

Subsection 5.5.1 discusses how to calculate the participation rate and proportion of non-passholders at each employer. The other component that is important to consider for a Mobility Pass is the amount that passholders use transit. This is determined through the use value. As aforementioned, the use value is the amount a monthly passholder would have spent on transit had they purchased each of their trips individually. Figure 5-18 shows boxplots for the use value of employees for employers with between 100 and 1000 active cards. Note that the use value is only calculated on LinkPasses and Local Bus passes, as the data uses the automatic fare collection (AFC) system, used on the bus and subway network. The horizontal blue line indicates the cost of a LinkPass during this analysis period (\$84.50). As can be seen, most employers have more than three-quarters of their employees use their monthly passes at a lower use value than the cost of the LinkPass.

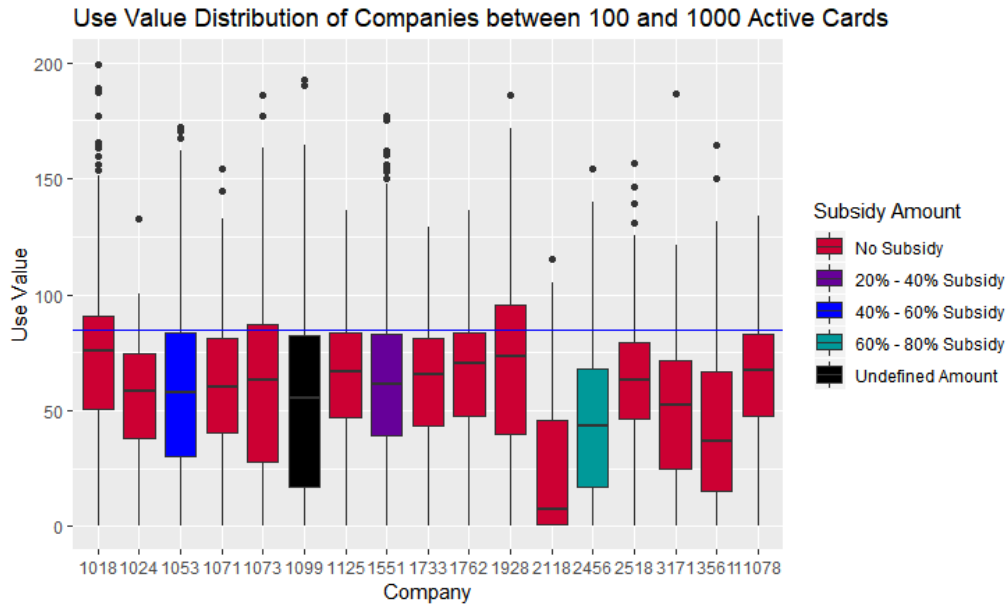


Figure 5-18: Use value distribution of companies with between 100 and 1000 active cards

The low use value is normal among Perq employees. (Kamfonik, 2013) found that Corporate Program employees were likely to have use values below people who purchase monthly passes through retail. This is in large part due to the subsidies that Corporate Program employees get from monthly passes. Even for employers who do not offer a transit subsidy, all Perq employees benefit from the pre-tax payroll deduction, which saves around 30-40% of the monthly pass. Additionally, the monthly passes can be auto-renewed through the Perq Program. In fact, many employees auto-renew their monthly pass even when they know they will be on vacation or not take transit as much one month, simply out of convenience.

A Mobility Pass would cost the employer the per-trip amount that employees take, rather than the cost of the monthly pass. While many employees would use transit below the cost of a transit pass, others are heavy transit users. For example, some employees would have spent over \$150 in a month had they purchased each trip individually rather than the \$84.50 for a LinkPass. These employees would cost the employer more than the cost of a monthly pass. Employers are often more nervous about the high-use employees when considering a Mobility Pass option.

5.5.3 Worst-Case Scenario

The Worst-Case Scenario analysis looks at the impact on revenue if all companies switched to the Mobility Pass. The worst-case scenario occurs if there is no ridership growth and everyone who currently uses a LinkPass or Local Bus pass through the Perq Program maintains their current use value. Thus, the worst-case scenario is the difference between the revenue made from LinkPass and Local Bus pass sales and the use value of those active cards. While the worst-case scenario is not a likely outcome, it helps put the revenue risk for the MBTA into perspective. Table 5-5 shows the current revenue, use value, and difference by company size in the Corporate Program. Under the worst-case scenario, if all companies were to switch to the Mobility Pass there would be a monthly revenue loss of \$2,067,811, 66% of which is from companies that have over 1000 active cards. This difference reflects the fares before July 2019. Including the fare increase, the total difference

becomes over \$2.2 Million per month. However, note that two employers with over 1000 active cards are the 3rd party administrators (WageWorks and Edenred). If the third-party administrators are assumed to have similar size distributions as the rest of Perq, then the employers with over 1000 active cards would account for roughly 50% of the revenue decline in a worst-case scenario.

Table 5-5: Worst-case scenario if all Perq employers switched to the Mobility Pass

Company Size	Revenue Change		
	Revenue	Use Value	Difference
< 10	241,017.80	188,748.70	(52,269.10)
10 to 25	374,600.00	283,859.50	(90,740.50)
25 to 50	426,400.30	322,155.50	(104,244.80)
50 to 100	396,578.00	303,075.60	(93,502.40)
100 to 1000	1,185,291.00	818,687.10	(366,603.90)
Over 1000	4,858,716.00	3,498,265.10	(1,360,450.90)
Total	7,482,603.10	5,414,791.50	(2,067,811.60)

It is also useful to see the worst-case scenario on a per-company basis, since, as seen in the use values, some companies would have larger revenue implications than others. To help illustrate the worst-case across companies, Figure 5-19 shows the difference between the revenue currently generated and total use value for each company. Logically, the companies with the most active cards are the ones with the highest difference between use value and revenue. The biggest revenue loss in the worst-case scenario by any one company is just over \$150,000 per month. None of the companies below 50 active cards have a greater difference than \$2,000, illustrating how low risk those individual companies are compared to the largest companies in the Corporate Program. However, while the largest companies have the greatest difference, it is mostly because they order so many cards. While almost all companies would earn less revenue for the MBTA in a worst-case scenario, a few actually have use values that are greater than the cost of the monthly passes purchased, showing how they would actually increase revenue for the MBTA under a Mobility Pass.

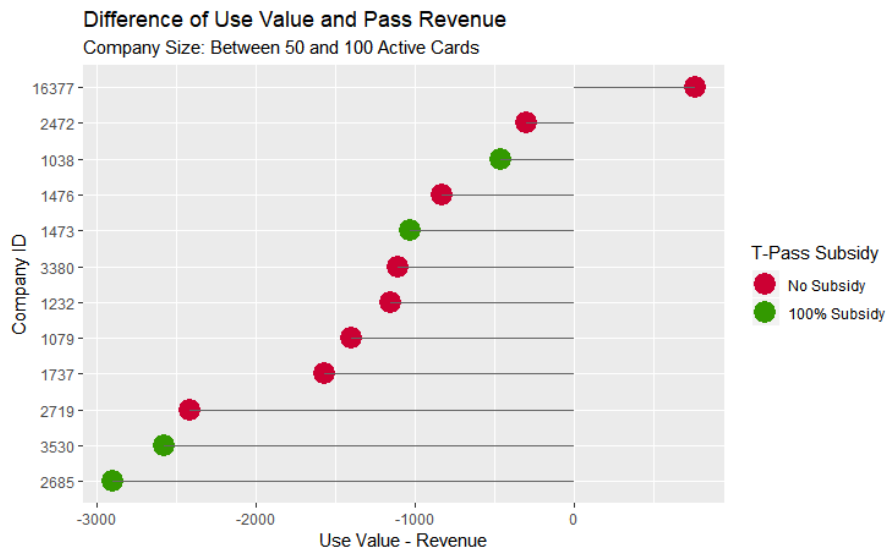


Figure 5-19: Difference between the use value and monthly pass revenue for employers between 50 and 100 active cards

5.5.4 Using MIT Pilot to Estimate Ridership Growth

With only one current case study of ridership change from the Mobility Program (MIT), it is difficult to fully understand the ridership growth from companies switching to the Mobility Pass. For this reason, multiple attempts were made to best estimate the ridership growth for companies currently in the Corporate Pass program. The different analyses show similar results, which helps frame a range of potential ridership growth estimates. The growth in ridership can mostly be attributed to two variables: the number of non-passholders at a company and the ridership growth from the non-passholders. The reason for different ridership growth estimates is because of a lack of information from companies. While we currently know the number of monthly passes sold per company and the total number of employees at each company (from the survey), we do not know how many people use the T not through the Corporate Program.

The most uncertain variable is the number of current non-passholders who are still using the T. This metric is important since their current use contributes to revenue the T is receiving. However, with only one case study to work with, it is difficult to know the number of people who are currently using the T outside of Perq, let alone how frequently they are using the T. In general, ridership growth can be estimated from MIT's increase in transit use from 2014 to 2016. Using the 2014 and 2016 Commuter Surveys at MIT and linking responses to individuals, average transit trips on the trip diary can be compared by passholder type (Table 5-6). The difference in weekly public transit use for non-passholders increased from 0.38 to 0.63 days per week after the Mobility Pass was introduced. Assuming the person also took public transportation returning home, the difference is doubled to calculate the increase in weekly public transit trips ($0.245 * 2 = 0.49$). There are roughly 4.3 weeks per month, so multiplying the weekly trips by 4.3 produces the monthly trips taken ($0.49 * 4.3 = 2.1$). If we assume the trips were taken on a subway, where the price is \$2.25, then the increase in monthly use value from non-passholders is \$4.73 ($2.1 * \$2.25 = \4.73). This increase in use value already accounts for the existing transit use of non-passholders (0.38 weekly trips in 2014) and averages across all non-passholders so we do not need to estimate how many non-passholders also use the T.

Table 5-6: Weekly public transit use from trip diary (MIT)

	Category	Mean PT	Count
2014	All Employees	1.86	6386
	No T-Pass (still worked 2016)	0.38	2326
	T-Pass (still worked 2016)	3.53	1984
	Left before 2016*	1.93	2076
2016	All Employees	2.16	5308
	No T-Pass (worked in 2014)	0.63	1909
	T-Pass (worked in 2014)	3.40	1688
	New since 2014	2.64	1711

*Includes employees who are still at MIT but work at Lincoln Labs/are not Benefits Eligible

Table 5-7 shows the calculations for all employee groupings. While the increase in monthly use value increased even more for all employees (\$5.68), this is because new employees had a drastically higher increase in use value. The new employee category is so large because of the large churn at MIT from postdocs and administrative staff. Hartnett 2016 found that new employees at MIT lived closer to campus and have lower levels of car ownership. Since new employees often start with lower salaries

than the existing staff, they are more receptive to major transportation benefits such as the Mobility Pass. Thus, considering the impact new employees will have on the Mobility Pass is important to include in the analysis as well. New employees come from two streams: company growth and churn. In MIT's case, the majority of the new employees are a result of churn with a slight increase in growth. It is estimated that the ridership growth is mostly attributed to the churn (since most new employees are part of the churn) and assume other companies have similar percentages in churn. At MIT the churn rate of employees is roughly 30% every two years (calculated from the biennial MIT Commuter Survey). An estimate of 25% churn is used for other companies since universities may have higher churn due to postdocs.

Table 5-7: Change in monthly use value from 2014 to 2016 (MIT)

	Difference	Weekly Trips (x 2)	Monthly Trips (x 4.3)	Monthly Use Value (x \$2.25)
All Employees	0.29	0.59	2.52	5.68
No T-Pass	0.24	0.49	2.10	4.73
T-Pass	-0.13	-0.26	-1.10	-2.47
Left/New	0.70	1.41	6.06	13.64

It is also important to explore whether the new employees were more likely to purchase monthly passes or not. Table 5-8 shows the percent of employees in 2014 who left before 2016 that purchased a monthly Pass through the Corporate Program. As Table 5-8 shows, the employees who are part of churn had a similar pass distribution as all employees at MIT (both around 36-38% of passholders). If churned employees had fewer or more passholders than the company-wide average, then an additional step would have to be conducted to account for the differences in churn among passholders and non-passholders. The only information known from employers are the behaviors of passholders and, for those employers who answered the survey, the total number of employees at the company (and, therefore, the number of non-passholders).

Table 5-8: Percent passholders from all employees and churned employees

2014 MIT	All Employees		Left Before 2016	
Passholder	3845	35.8%	780	37.6%
Non-Passholder	6882	64.2%	1296	62.4%
Total	10727	100.0%	2076	100.0%

Since churned employees purchase monthly passes at a similar rate to returning employees, it is assumed that 25% of non-passholders at a company will be replaced after the Mobility Pass is offered. As aforementioned, 25% churn is assumed at these employers given that MIT has a 30% churn every two years, which is expected to be higher than the churn from other employers given the typical structure of universities. The ridership growth for companies is a \$4.73 use value increase from 75% of non-passholders (existing employees) and a \$13.64 use value increase from 25% of non-passholders (new employees). Current passholders are assumed to maintain the same use value. Although the MIT survey showed a decrease in use value from existing passholders (most likely attributed to no longer meeting a pass multiple), this decrease is counteracted by the large use value increase by new employees. For example, if 75% of passholders (existing employees) decrease their use value by \$2.47, that is balanced by a \$13.64 increase from 25% (new employees) of passholders ($0.75 * 2.47 < 0.25 * 13.64$).

5.5.5 Mobility Pass Perq Expansion

Table 5-9 shows the worst-case scenario (No Growth) and the ridership growth estimate (NonPassholder Growth) assuming that 75% of non-passholders increase their use by an average of \$4.73 and 25% increase their use by \$13.64. It is scaled up to the overall Perq Program, assuming that the companies within the third-party administrators are similar in size distribution as the rest of Perq. Scaling was done by dividing the Non-passholders Growth column by the percent of the sample compared to the overall population ($\$8,193 / (-\$9,228 / -\$52,269) = \$46,411$). The percent difference of the growth was used to scale since using current revenue would ignore the average use value of the companies using the system. The difference incorporates both the revenue and the use value and should better reflect growth for the companies where there is not enough information.

Table 5-9: Worst-case scenario vs. non-passholders growth scaled up to all companies

Scaled Up (Including 3rd Parties)		
Company Size	Revenue Change	
	No Growth	NonPassholders Growth
< 10	(78,613.12)	69,801.88
10 to 25	(136,474.39)	37,733.73
25 to 50	(156,784.96)	(7,354.66)
50 to 100	(140,628.31)	(80,418.54)
100 to 1000	(551,375.01)	60,577.85
Over 1000	(1,003,935.82)	(83,903.03)
Total	(2,067,811.60)	(3,562.76)

Overall, the ridership increase was almost enough to breakeven across all companies. In the worst-case scenario, the Mobility Pass would cause a revenue decrease of over \$2 million per month. However, it is unlikely that the worst-case scenario would manifest. Instead, if all companies in Perq switched to a Mobility Pass and had similar ridership growth estimates as MIT, then the Perq revenue would only decrease by \$3,500 per month. This slight decrease in revenue is the result of significant ridership growth and increased transit availability to employees in Greater Boston. Figure 5-20 illustrates the revenue growth for employers with over 1000 active cards. The lighter circle on the left indicates the worst-case scenario, or the difference between the use value and revenue currently. The darker circle on the right indicates the new difference in use value and revenue assuming ridership growth similar to MIT. The employers with the greatest growth are the ones with the lowest employee participation rate. While some employers would result in a significant increase in ridership and revenue, others would have modest gains.

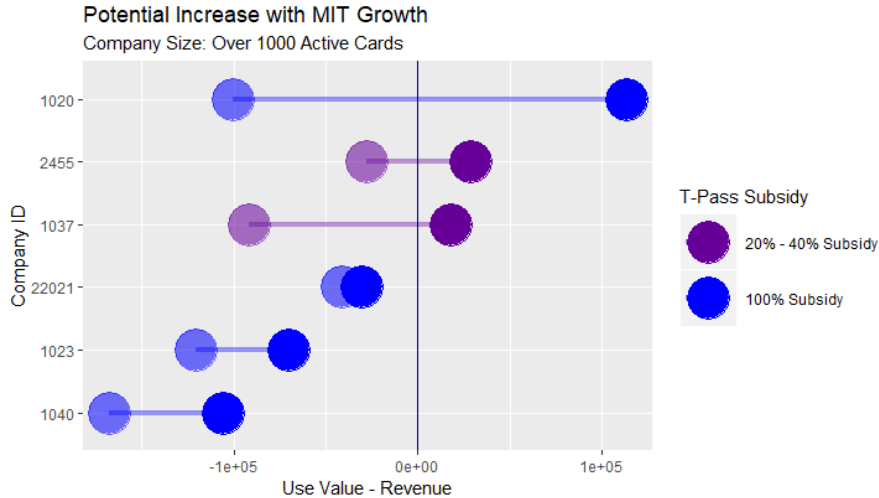


Figure 5-20: Use value minus revenue with and without ridership growth using a \$4.73 increase from 75% of non-passholders and a \$13.64 increase from 25% of non-passholders for employers with over 1000 active cards

5.6 COVID-19 Impacts on Perq

Following the original stay-at-home order in March 2020, there was a lot of uncertainty on how long the work-from-home and restricted travel would last. Early assumptions were that the stay-at-home would only last a few weeks or months. The MBTA, in an effort to avoid significant withdrawals from employers in Perq, implemented a reimbursement policy where unused (inactive) monthly passes would be reimbursed. This was done to allow employers to remain in Perq without having to pay for unused transit passes.

The billing process for Perq, before the pandemic, involved employers adding monthly pass orders for their employees in the Perq system by the 15th day of the preceding month. April monthly passes would be ordered on March 15th to provide enough time to place the order. Since the stay-at-home order was given days before the deadline in March 2020 and there was a lot of uncertainty on how long the order would last, most employers did not change their orders for April 2020. The MBTA, however, implemented their reimbursement policy for Perq. This meant that all monthly passes that were unused in April 2020 were reimbursed to the employer. The reimbursement process was tedious and involved the MBTA fully crediting employers for their orders in the preceding month and then applying a charge for the used cards. For all monthly passes that were ordered by March 15th, 2020, those that went unused in April 2020 (approximately 75,000) were reimbursed by May 15th, 2020. Note that the MBTA had to reimburse passes two months after they were ordered to check the card activity for the full month of use. The MBTA has kept this policy until April 2021, when they reverted back to the previous policy.

5.6.1 Perq Overview and Trends

Figure 5-21 shows the aggregate number of monthly passes (on the bus and subway system) that were ordered and used before and during the COVID-19 pandemic in Perq. Before the pandemic, roughly 7% of passes ordered were never used. Some of these passes were “blank cards,” which are inactive passes that companies can order and activate during the month, in case an employee needs a pass for that month. However, some of those unused passes were purchased and never used. Before the stay-at-home order was enacted, Perq revenue for bus and subway passes was generated from monthly pass orders. After April 2020, Perq revenue was generated based on used passes. Similar to

ridership trends, there was an initial drop in usage of almost 90%. However, because buses implemented a rear-door boarding between mid-March and mid-July, the number of active monthly passes more accurately reflects subway ridership (specifically where faregates are located). Since July 2020, once fare collection resumed on fareboxes, the percent of passes used compared to pre-pandemic numbers were around 25% per month.

The reason the MBTA offered reimbursement to employers was to prevent a massive departure of employers from Perq, causing a significant backlog for the MBTA. Instead, by allowing employers to be reimbursed for unused passes, the rate of employers canceling their orders with Perq was minimized, as is evident from the “Passes Ordered” line in Figure 5-21. In April 2020, monthly pass orders decreased slightly from 91,300 to 85,300. The next month saw the largest drop in new orders from 85,300 to 68,200. These declines, while being the highest ever experienced in Perq, were much lower than the decline in usage, which went from 81,200 to 10,700 from March to April 2020. Therefore, offering a reimbursement helped the MBTA avoid massive turnover.

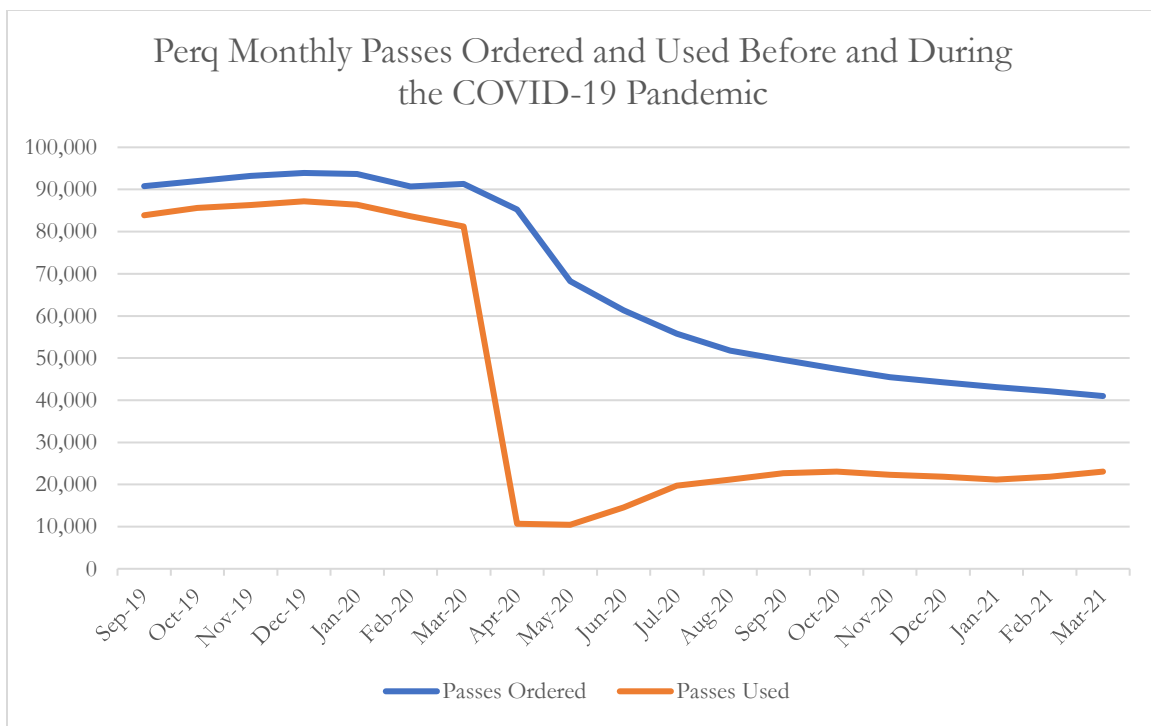


Figure 5-21: Perq monthly passes ordered and used (September 2019 to March 2021). April 2020 was the first month of the new reimbursement policy, which ended in April 2021 (not shown).

Commuter rail passes in Perq operate differently, largely due to the inability to track ridership on commuter rail monthly passes. Commuter rail monthly passes ordered through Perq are called “Flash Passes.” This is because the pass is a monthly LinkPass with a sticker that indicates on which zones the commuter rail pass is valid. The pass is “flashed” to commuter rail conductors for validation. Perq employers order commuter rail passes each month for the employees who sign up for a commuter rail pass. If an employee decides they do not want to travel that month, they have to physically mail their commuter rail pass back to the MBTA. Figure 5-22 shows the commuter rail Flash Passes that were purchased and returned each month from September 2019 to March 2021. The combination of purchased and returned passes indicate the number of Flash Passes ordered each month. Before the stay-at-home order, there were roughly 38,000 Flash Passes purchased each

month with less than 1% being returned. In April 2020, just over half of all Flash Passes were returned as employees were not taking commuter rail. In the following months, the number of Flash Passes ordered decreased steadily as did the number of passes returned. By March 2021, the number of Flash Passes purchased was down to 4,600.

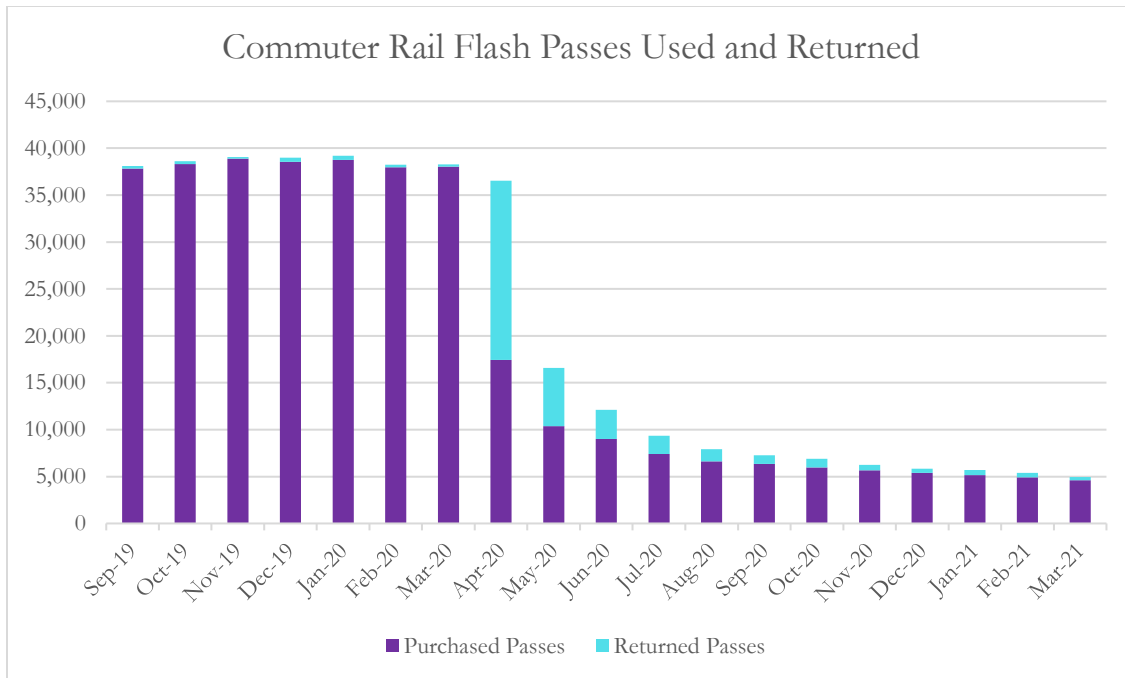


Figure 5-22: Commuter rail Flash Passes that were used and returned each month. The total of both indicate the number of Flash Passes ordered for that month.

The decline in pass sales means revenue also suffered significant losses from the pandemic. Before the stay-at-home order in March, commuter rail revenue was consistently over \$9.5 million and bus and subway revenue was above \$8 million (see Figure 5-23). Despite selling around 60% less commuter rail passes as bus and subway passes, the relatively high price of commuter rail makes the revenue higher than from bus and subway. Since the policies were different on commuter rail and bus and subway passes, revenue had different trajectories at the early stages of the pandemic. Commuter rail revenue declined by 56% in April 2020 while bus and subway revenue declined by 88%. Since then, commuter rail revenue has continued to decline as employees cancelled their orders and returned Flash Passes. Bus and subway revenue, however, increased from April to October 2020 as employees began traveling again. Bus and subway revenue dipped slightly in the winter and rebounded a little in the Spring of 2021.

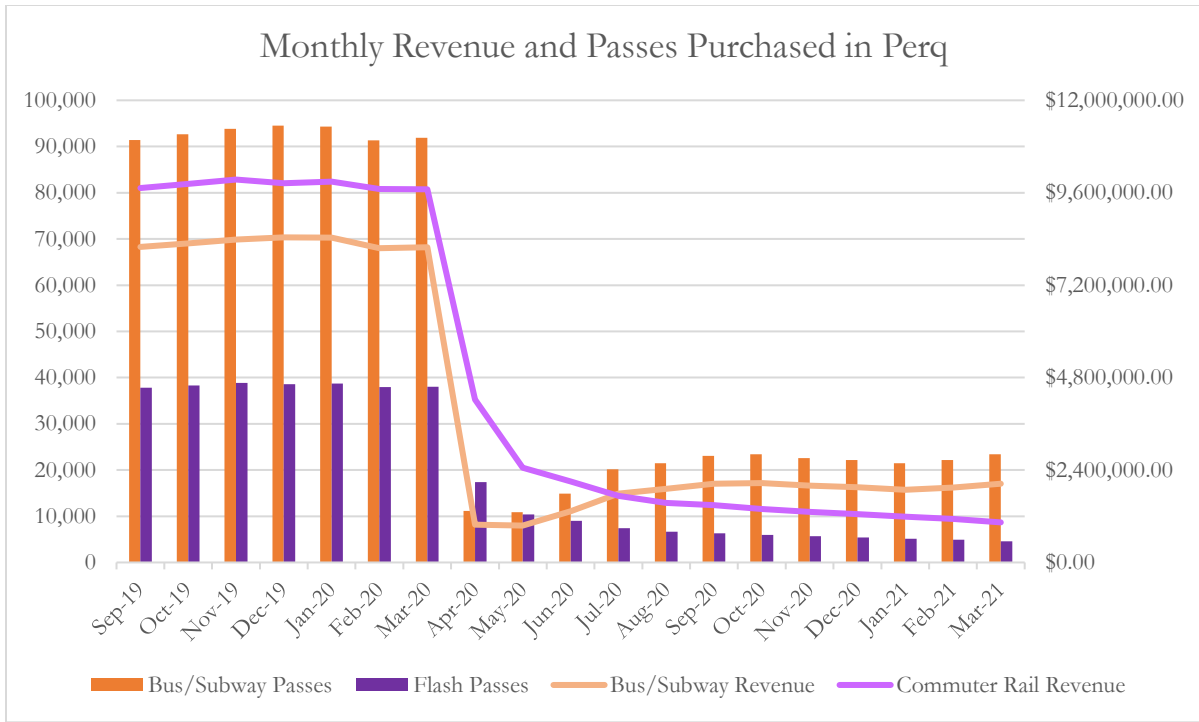


Figure 5-23: Monthly revenue and number of passes purchased in Perq for bus/subway and commuter rail from September 2019 to March 2021.

5.6.2 Company Characteristics During COVID-19

Given that Perq employers and ridership declined significantly during COVID-19, the company make-up has also changed significantly. Some of the largest employers, especially those located downtown, shifted to remote work, which had significant effects on Perq revenue. However, many of the largest employers in Perq are hospitals since Boston has a significant healthcare industry with many prominent hospitals. Thus, many of the largest employers which were hospitals remained active in Perq throughout the pandemic. Figure 5-24 shows the cumulative distribution function of employer sizes by the number of active cards during the COVID-19 pandemic. Whereas before COVID-19 the bottom 50% of employers had 7.5 active cards per month, now the smallest 50% of employers only had 2 cards per month or less. Pre-COVID-19, the smallest 90% of employers had 53.5 active cards per month or less whereas that number dropped to 15.5 during the pandemic.

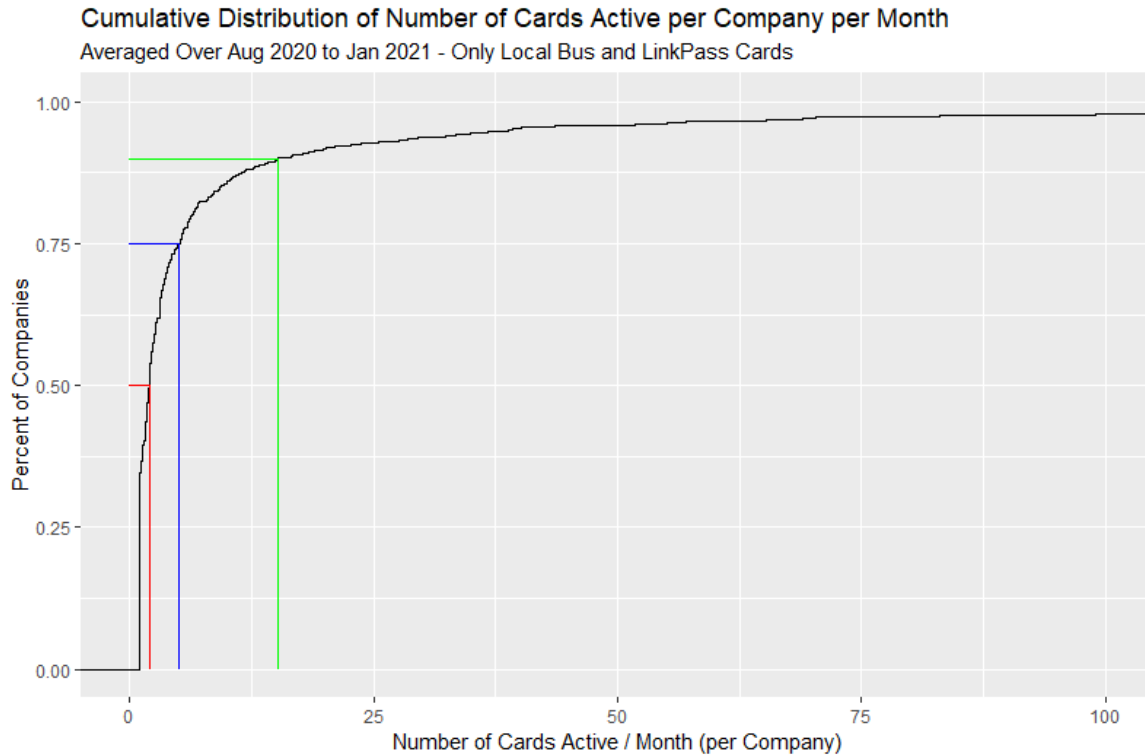


Figure 5-24: Cumulative distribution function of total cards active by companies in Perq

The smaller employer sizes, by number of active cards, reflects the decreased ridership during COVID-19. However, since many of the largest employers are hospitals that remained in operation, the revenue distribution still was dominated by the largest employers. Figure 5-25 shows the distribution of companies and revenue categorized by the number of active cards per month. Before the pandemic, roughly 58% of employers had less than 10 active cards per month. That number increased to 85.8% during the pandemic. Additionally, employers with over 50 active cards made up around 10% of the employers and nearly 80% of the revenue (excluding third party providers) in 2019. In 2020, during the pandemic, employers with over 50 active cards only accounted for around 4% of employers but still contributed to 80% of the revenue. This is primarily because of the hospital systems that continued commuting during the pandemic that employ thousands, many of which commute to the hospital on transit.

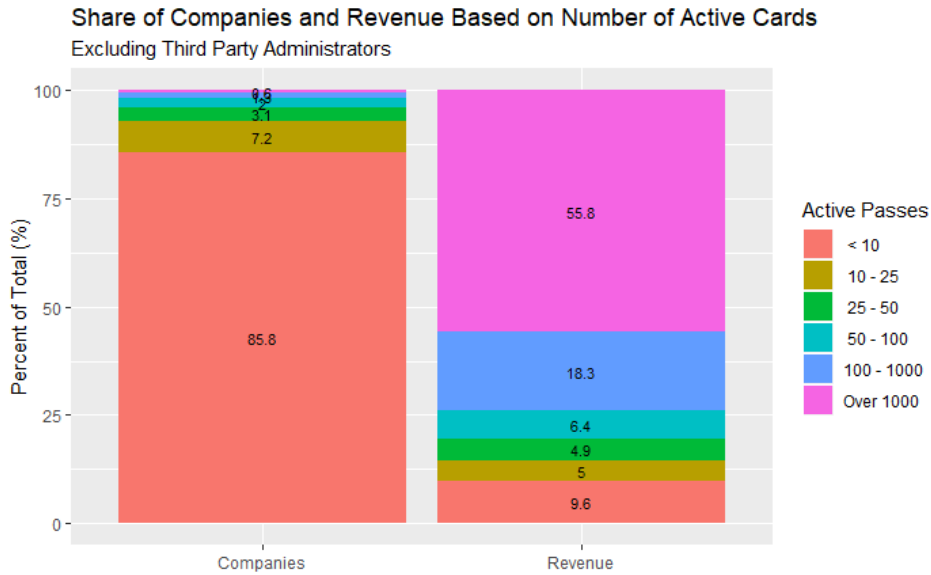


Figure 5-25: Share of all companies and revenue based on number of active cards (not including third party administrators)

5.6.3 Use Value Shifts

The temporary Perq sales system charged users whenever they used their Perq monthly pass during COVID-19 (April 2020 to March 2021). Employers were charged the full pass price for any employees who used their pass, even if only for a few trips during a month. Figure 5-26 shows the use value distributions for Perq before COVID-19 and during the pandemic. The median use value during the pandemic was \$48.00 (red vertical line). The median use value of the pre-pandemic ridership was \$68.70 (blue vertical line). The LinkPass fare is \$90 (black vertical line), meaning that over 50% of Perq employees use their LinkPasses less than the cost of the pass itself. The decreased ridership among Perq users is likely from the increase in work-from-home, the reduction in leisure activities and events, and the travel restrictions.

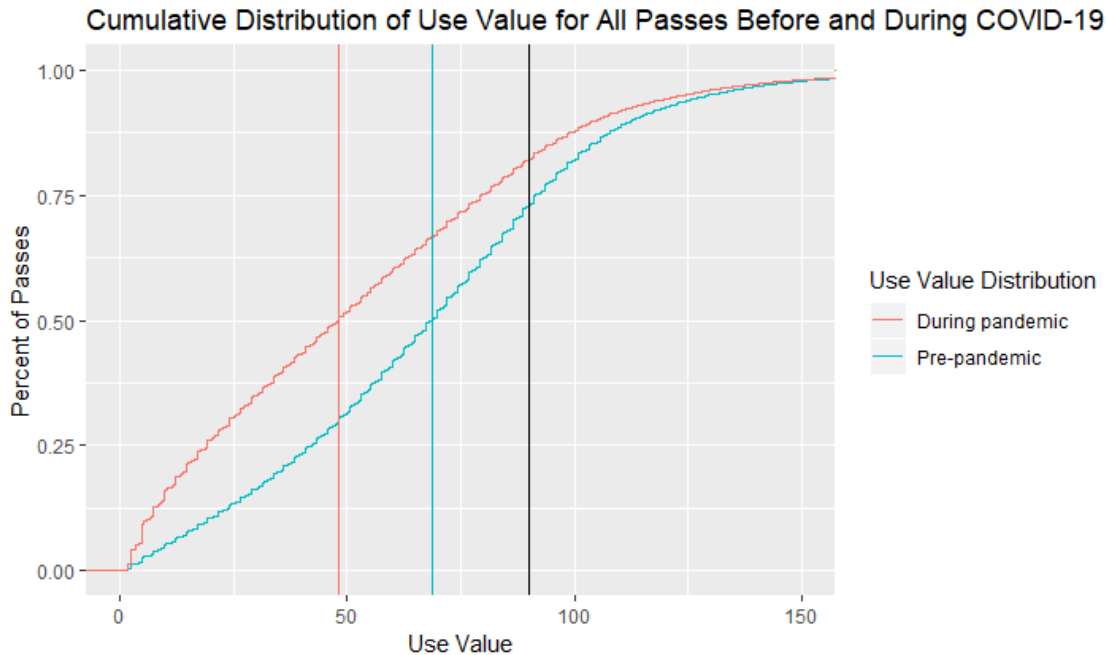


Figure 5-26: Cumulative distribution of the use value for all Perq users before the pandemic (Sept 2019 to Feb 2020) and during the pandemic (Sept 2020 to Feb 2021)

A significantly reduced average individual use value suggests that this is a prime opportunity for the MBTA to expand the Mobility Pass. The cost to employers would be reduced due to the low usage of the passes, which would encourage more employers to enroll in a Mobility Pass. Additionally, the Mobility Pass would provide free additional trips to employees, encouraging them to take transit. Getting employees on transit should be a top priority for the MBTA, especially as employees begin commuting to the office again. Driving has only declined by around 10% year-over-year at the end of 2020 based on vehicle miles traveled (Federal Highway Administration, 2020). The MBTA, however, has yet to surpass 50% of pre-COVID-19 ridership levels system-wide. With the pattern break of the pandemic, it is crucial that employees are encouraged to take transit as offices open up. People tend to stick to travel habits once they are established, making it all the more important to move them into transit early into reopening of offices.

5.7 Using the Mobility Pass for a Rapid Recovery

Ridership on Perq has declined significantly during the COVID-19 pandemic. It is unclear how soon ridership will return to pre-pandemic levels, if at all. With modal shifts to cars and cycling, as well as a potential increase in working-from-home, the MBTA estimates years until ridership and revenue reach pre-pandemic levels. In fact, the estimated fare revenue for Fiscal Year 2026 is 11-34% below the baseline (O'Hara & Panagore, 2021). This indicates a long and gradual return to pre-pandemic ridership levels. Thus, the MBTA would benefit from increasing ridership. This is especially true as downtown offices open up to their employees again. The pattern break caused by COVID-19 is an opportunity for the MBTA to capture ridership on its system as employees choose a travel mode to get to work. A discounted fare product that fits the travel behaviors of riders would help attract and retain ridership, eventually leading to increased usage as commuting resumes in the near future.

To better understand the anticipated return to the office, an employer survey was distributed to an employer panel in December 2020. At the early stages of the pandemic, the MBTA created an

employer panel, made up primarily by the employers in Perq, and asked various questions about the anticipated return to the office every two months. This panel has helped the MBTA gauge the uncertainty from employers and their anticipated return to the office, if there was one. The bimonthly employer survey that was distributed in December 2020 included questions around the transportation policies that employers had offered in the past and were currently offering, given the reduced travel. Subsection 5.7.1 goes into further detail of the employer survey and their responses.

The responses from the December 2020 employer survey help frame the potential work-from-home policies as employers return to the office. The survey also asked about parking availability and concern for parking as employees return to the office. Many employees who still commuted to the office shifted to driving during the pandemic out of concern of contracting COVID-19 on transit, despite evidence that suggests transit is not a significant contributor to the spread of the virus. With a significant portion of “traditional” working hours employees (i.e. 9am to 5pm) working from home during the pandemic, congestion on the streets decreased significantly, especially early in the pandemic. Decreased traffic also helped contribute to a shift of employees to driving to work. This shift has led many employers to be concerned about parking availability as they return to the office.

An analysis of potential ridership growth from a Mobility Pass is calculated based on the survey and data of pre-pandemic and during the pandemic Perq ridership patterns. As previously mentioned, the MBTA anticipates reduced ridership at least until the summer of 2026. This analysis examines the potential ridership gain that would come from a Mobility Pass option for employers. Subsection 5.7.2 discusses this analysis in more detail.

5.7.1 Employer Panel Survey, December 2020

In July 2020, the MBTA initiated an Employer Panel designed to gauge the current work-from-home policies of employers and their thoughts on their anticipated return to the office. The survey was distributed roughly every other month to pulse employer thoughts through the various stages of the pandemic. In December 2020, the MBTA distributed the third round of the Employer Panel Survey (EPS) to companies both in the Perq program as well as those not in Perq, but still in the Greater Boston region. In total, 56 employers responded to the survey, of which 53 completed the entire survey. These employers employ over 57,000 workers.

Eight of the employers who responded to the December 2020 EPS had at least 1,000 employees and account for 91.5% of the employees working for the companies who responded to the December 2020 EPS. Of these eight, four are Perq members, which all responded to the May 2019 Corporate Program Survey. Since employees translate to existing and potential ridership, all responses will be shown in terms of percent of employees affected. All of the responses are also adjusted to reflect any representation bias that we can capture through an analysis of the pre-COVID (and more representative) May 2019 Corporate Program Survey. (See the Appendix D:for information on scaling process).

Since few companies impact most employees, the following survey responses are shown in terms of percent of employees affected. This is determined by multiplying each response by the number of employees at each company. A scaling method is then applied to the number of employees to more accurately reflect the population of interest from this survey. All but two employers from the December 2020 Survey listed the number of employees at their company. Only those who listed the number of employees are shown in the responses described below (N = 51). Figure 5-27 shows the responses from employers when asked which transportation modes employees can receive pre-tax

payroll deductions, then scaled to the number of employees who are covered by the employer’s policy and also separated by their employers stated return to work policy. Almost 97% of employees are offered pre-tax payroll deductions for public transit, and 87% of employees are offered pre-tax payroll deductions for parking. From the December 2020 Survey, over three-quarters of employers reported offering pre-tax public transit benefits while 43% of employers stated they offer pre-tax parking payroll benefits. This disparity between the proportion of employers who offer certain pre-tax benefits and employees who are offered these benefits is due to the fact that the vast majority of the largest employers offer parking and transit payroll deductions. Only 1.5% of employees are not offered a pre-tax payroll deduction for any transportation mode. This follows what was found from the May 2019 Corporate Program Survey where larger employers are more likely to offer pre-tax payroll deductions and subsidies than smaller employers, likely due to the bandwidth available to process these benefits.

In total, 44% of employees work at places where the employer anticipates a full return to the office after the pandemic subsides. There are another 21% of employees whose employers anticipate a partial return to the office, either with staggered days or only a subset of the workforce returning. Only two percent of employees are working at places that anticipate remaining fully virtual. Almost a third of employees have employers who are uncertain of how they will return to the office. This overall breakdown is fairly representative among employers who offer pre-tax payroll deductions for transit and parking, signaling minimal differences among those who offer one pre-tax benefit over another.

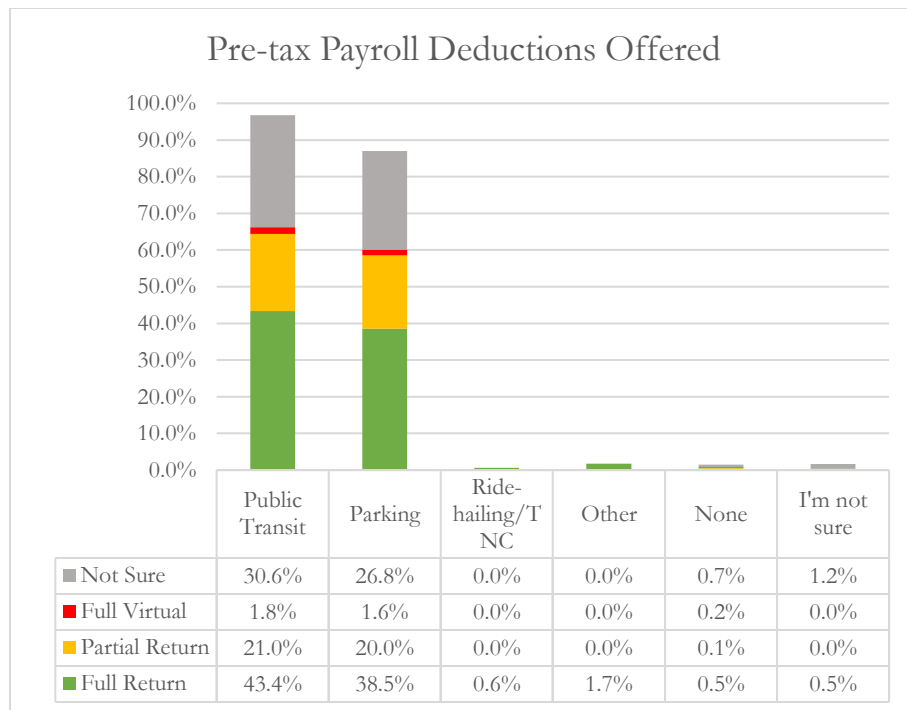


Figure 5-27: Pre-tax payroll deductions by transportation mode by return to office intention

Employers were asked if their organization was concerned about parking availability between now and a return to the office. There are around 63% of employees working for employers who have concerns about parking upon returning to the office. More importantly, over a third work at employers who are actively looking to expand parking availability, either through new garages or leases. Those (two) large employers who are actively seeking new parking are also planning on fully

or partially returning to the office, while those who are concerned about parking availability but are not actively adding parking spaces are much more uncertain about how they plan to return to the office, if at all. Of these employers who answered the December 2020 Survey and are concerned with parking availability, three-quarters have at least 100 employees. This has major implications in land use and transit ridership when employees return to the office. Parking availability and subsidies will likely draw many employees away from transit and to driving alone instead. These employers could, however, reduce anticipated parking demand with higher transit subsidies and lower parking subsidies. For that reason, these employers would be ideal candidates for a Mobility Pass, which would offer free transit to the employees and reduce parking demand. It should be noted that one of the employers who indicated a concern for parking also indicated that, due to commuter rail service cuts, they were providing free parking to commuter rail passholders. Parking availability concerns and decisions to increase parking availability for employers are also influenced by transit availability and service provision. Potential service cuts may increase pressure on employers to offer parking subsidies and increase parking availability, both of which would have long-lasting and damaging impacts on transit ridership.

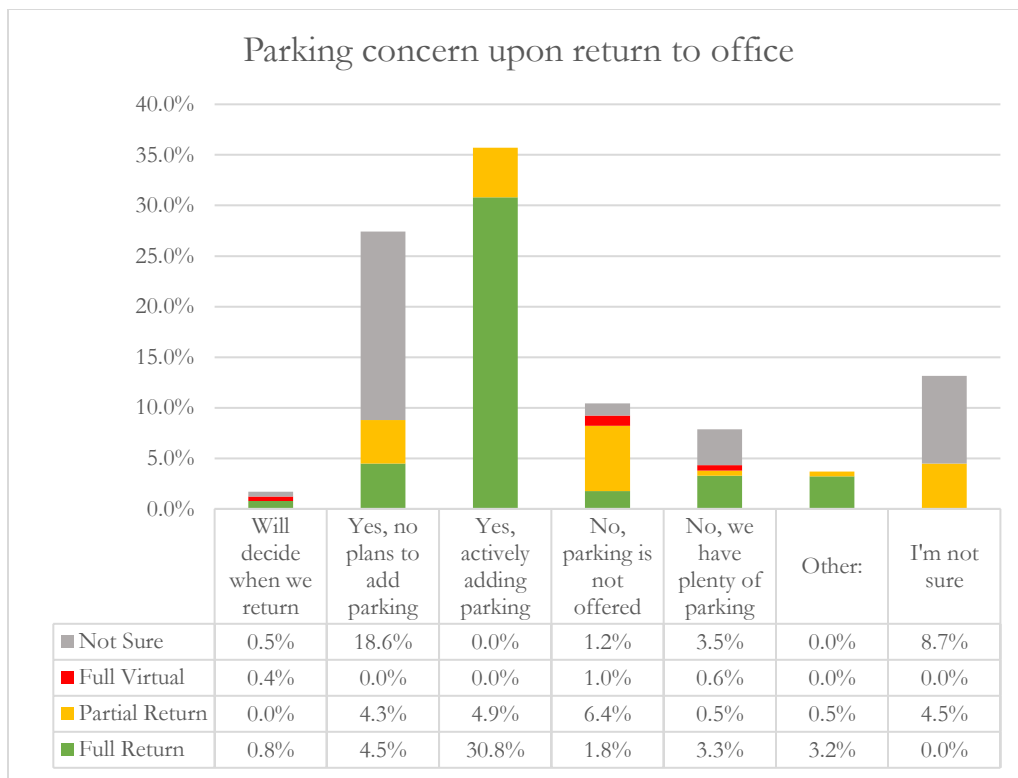


Figure 5-28: Parking concern among employers by employees affected and by return to office policy

Of the employers who filled out the December 2020 EPS, nine of them (17%) stated that their transportation benefits have changed since the pandemic began. The nine organizations, however, employ only 5% of the employees represented in the survey, suggesting they are smaller employers. One of the nine stated that the change was permanent, one was uncertain, and the remaining seven indicated that the changes were temporary, most of which were uncertain as to how long the changes would be temporary. Six of the employers went from offering no parking benefits to offering reduced parking costs, three of which made parking completely free. The other three employers offer subsidies to reduce the cost of parking for employees. One employer went from offering full (100%) MBTA LinkPass subsidies and \$270 for Commuter Rail to suspending all

MBTA subsidies. Another employer went from offering \$90/month, regardless of commuting method, to removing their transportation subsidies until after the pandemic. All of the nine employers indicated a portion of their workforce was working in-person, with eight of the nine indicated somewhere between 1-25% of their workforce was in-person (the last indicated 100% of their workforce was in-person). All but one of these eight employers also said the remote staff visited the office at least once a month. It is important to recognize that these employers constitute a small portion of employees and, therefore, a small portion of Perq and passholder ridership. For that reason, scenario analyses of Perq ridership could primarily rely on the May 2019 Corporate Program Survey when estimating the proportion of the Perq population that receives transit subsidies and parking discounts.

Finally, the December 2020 EPS asked employers why they offered the transportation benefits that they did (or will, once employees begin commuting). Employers were able to indicate as many reasons as they wanted, and responses are shown by number of employees impacted. The top three reasons indicated for offering their transportation benefits are to encourage sustainable transportation (73.6%), attract top talent (68.8%), and because of the transportation options nearby the office location (60.3%). This is useful to know in the sales pitch to employers when advertising the Mobility Pass. The Mobility Pass would advance sustainable transportation for workers by increasing the transit mode share among employees, would be a novel and attractive transportation benefits for top talent acquisition, and can be financially beneficial for the employer by reducing parking demand and reducing the cost of providing a “free” pass to all employees.

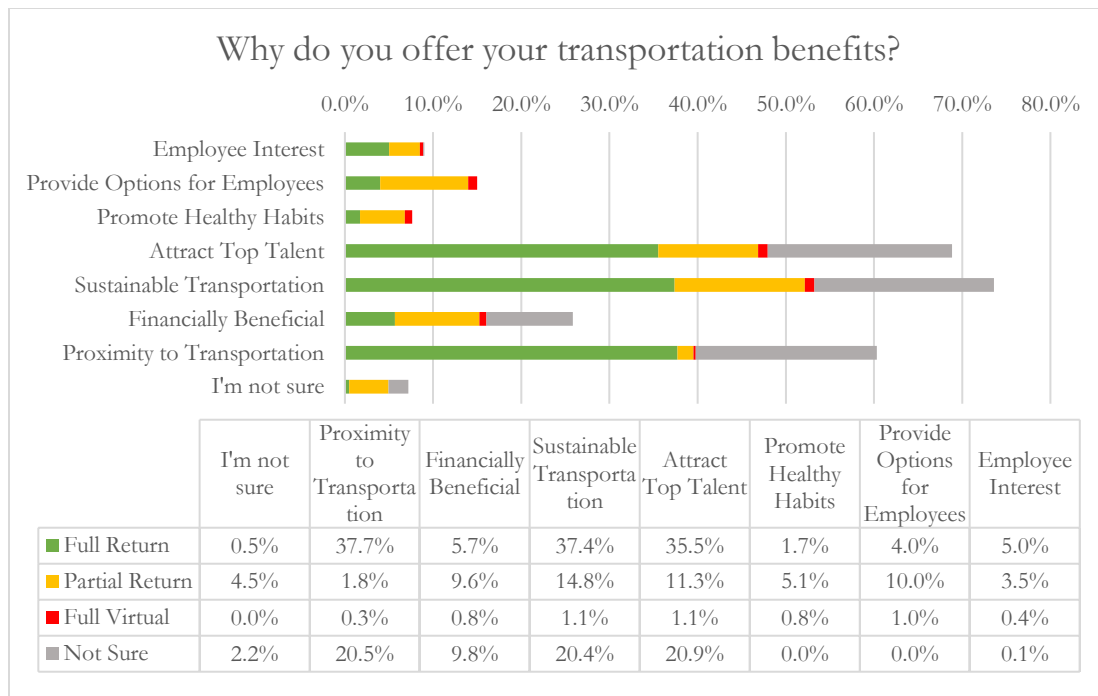


Figure 5-29: Purpose for offering transportation benefits to their employees by return to office policy

5.7.2 Estimating Post-Pandemic Ridership and Revenue

While there is still a lot of uncertainty around how commuting patterns and ridership will look in the years following the COVID-19 pandemic, it is still important to estimate the potential growth from a Mobility Pass. The December 2020 Employer Panel Survey helped frame the potential work-from-home policies as employers return to their offices. This section will expand on the survey by using it

to estimate the ridership based on four scenarios. The scenarios are based on the survey responses on return to work expectations with variations in the details of the general responses. Additionally, this analysis explores the potential benefits of offering a Mobility Pass to employers. The ridership and revenue implications from a Mobility Pass are compared to the counterfactual for each scenario. The counterfactual would be a business-as-usual approach where Perq remains the way it is.

Why would employers and the MBTA be interested in a Mobility Pass? For employers, the Mobility Pass is a discounted product for the benefit it provides. As was discussed with the MIT Pilot in Section 5.3, the cost of providing a LinkPass to every MIT employee would have been \$900,000 each month whereas the Mobility Pass, which effectively offers the same benefit, was around one-third of the cost. However, MIT previously offered a 50% subsidy for LinkPasses and under the Mobility Pass increased their subsidy to 100%. What convinced MIT to increase their subsidy? One motivating factor was the high cost of parking structures and the opportunity cost of using the parking spaces instead of new academic or research facilities. By offering free transit to all employees, MIT was able to reduce its parking demand, demolish deteriorating parking garages, and construct new buildings in their place. Another motivation for offering a Mobility Pass was for employee satisfaction and retention. Figure 5-9 from Section 5.3.2 showed a noticeable increase in the employee satisfaction at MIT with commuter benefits in the first year of the Mobility Pass. That increased employee satisfaction likely translates to increased retention and helps MIT attract top talent by offering free transit to employees.

So why would other companies want to offer a Mobility Pass? Some employers might have similar parking constraints as MIT. This is more likely true with the largest employers located in Boston where parking and real estate are scarce. The December 2020 Employer Panel Survey found around 63% of employees working for a company that is concerned about parking availability as people return to the office. Some employers might consider adding parking spaces for their office. However, that would be really expensive in Boston and would take up valuable real estate. Alternatively, employers could reduce parking demand by offering a Mobility Pass as MIT had done. The December 2020 EPS showed that around 74% of employees work at a company that offers their benefits to encourage sustainable transportation and 69% work at a company that is interested in attracting top talent. If employers wish to offer transportation benefits that encourage sustainable mobility and attract top talent, the Mobility Pass would be an ideal benefit to offer as it heavily discounts transit and is offered to all employees (under the universality condition).

Why should the MBTA offer a Mobility Pass to employers? That is the central question in this analysis, especially regarding how the Mobility Pass could be used as a way to speed up the bus and subway recovery. The process of estimating post-pandemic ridership growth begins by estimating the work-from-home policies from the employers. *Figure 5-30* shows the breakdown of employees and employers by the anticipated work-from-home policy. Note that a higher share of employers anticipated a fully virtual setting than the share of employees, meaning these were mostly smaller employers that did not plan on returning to the office. Assuming that the distribution of the uncertain employers is the same as those who responded, then 72.1% of employees would have a full return to the office, 26.6% of employees would partially return and partially work-from-home, and only 1.3% of employees would work fully remote. Although only 1.3% of employees were expected to remain virtual, that corresponds to roughly 12.8% of companies that plan on working remotely after the pandemic.

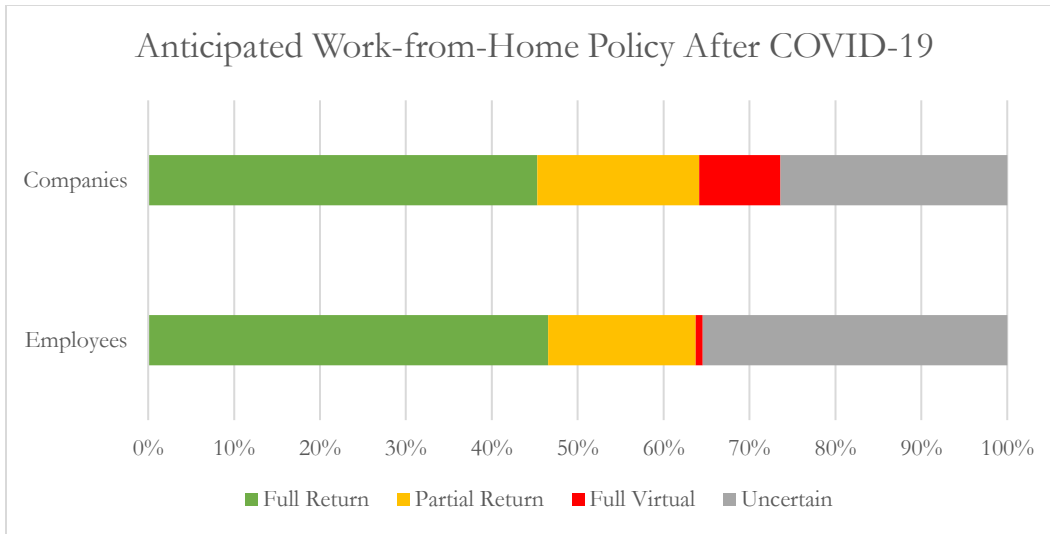


Figure 5-30: Anticipated work-from-home policy for employers for when the pandemic mostly subsides

This analysis uses a baseline ridership from September 2019 to February 2020 as it is the most recent data before the pandemic and accounts for the fare increase in July 2019. The six-month data is averaged out to account for seasonal variation and shifts in employer sizes (churn at employers). Post-pandemic ridership is estimated using the pre-pandemic ridership as a baseline and applying reductions in travel behaviors based on the scenarios and return-to-work policies from the December 2020 EPS. The first step is to estimate the employers that went completely virtual. To accomplish this, 12.8% of the employers were randomly removed from the analysis. However, since the 12.8% of employers only accounted for 1.3% of employees in the survey, it is assumed the smaller employers are more likely to go completely virtual. To address this, three of the four scenarios estimate a different employer size going fully virtual. The first and most optimistic scenario (Full Return) uses pre-pandemic ridership levels and does not assume any work-from-home changes. The second scenario (High Return) assumes that only employers that have less than 25 cards become fully virtual. The third scenario (Moderate Return) applies to all companies with fewer than 50 cards and the fourth scenario (Low Return) uses companies with less than 100 cards. Each scenario randomly selects 12.8% of all employers (within the respective sizes) and removes all employees from the analysis. The scenarios only vary by the size of employer eligible to be converted to remote work, which ultimately changes the number of employees that are estimated to become fully remote. A full breakdown of the ridership assumptions for the three scenarios (excluding the pre-pandemic ridership “Full Return” scenario) can be found in Table 5-10.

Table 5-10: Overview of assumptions for each ridership return scenario

	High Return	Moderate Return	Low Return
Fully Virtual	12.8% of companies with < 25 active cards	12.8% of companies with < 50 active cards	12.8% of companies with < 100 active cards
Partially Virtual	26% of employees traveling 30% less	26% of employees traveling 50% less	26% of employees traveling 70% less

	5% of employees leaving Perq	10% of employees leaving Perq	15% of employees leaving Perq
Full Return	10% of employees leave Perq	20% of employees leave Perq	30% of employees leave Perq

The next step is to estimate the partial return-to-office employees and employers. There are many potential ways in which employers could be partially at work and partially remote. For instance, an employer could consider being partially virtual as allowing employees to work from home at most once a week, or they could take partially virtual to mean only going to the office once a month. To account for the possible partial work-from-home policies, each scenario considers a different amount of remote work. The High Return scenario assumes a partial work-from-home of between one and two days per week by reducing ridership by 30% (1.5 days / 5 work days per week). The Moderate Return scenario assumes half of the days are work-from-home and the other half are in-person. Finally, the Low Return scenario assumes 70%, or between three and four days per week, are remote. For each of those scenarios, 26% of employees are randomly selected and their ridership is reduced based on the work-from-home assumptions from each scenario. The number of randomly selected employees is based on both percent of employees and employers estimated to be working partially remote from the December 2020 EPS, which found about 26% of both employees and employers to be partially remote.

Since some employers are moving to partial work-from-home policies, it is assumed that a portion of those employees will no longer participate in Perq. With reduced ridership, employees might not find it worthwhile to purchase a monthly pass and instead pay individually (pay-as-you-go) for trips. For the second scenario (High Return), 5% of total employees are assumed to no longer purchase Perq passes due to reduced travel. The third scenario (Moderate Return) assumes 10% of employees leaving Perq and the fourth scenario (Low Return) assumes 15% of all employees. Recall that the first scenario assumes a full return of ridership from pre-pandemic levels. The increase in the employees who no longer purchase monthly passes matches the increased work-from-home assumptions of each scenario. For example, the Low Return scenario assumes the work-from-home policies from employers requires workers to commute between one and two days a week. With such reduced ridership, it is likely that many employees would no longer benefit financially from a Perq pass, even with the pre-tax payroll deduction and potential employer subsidies. Therefore, 15% of employees, or 57.7% of the partially remote employees (15% / 26%), are assumed to leave Perq entirely. Traveling to work a few times per week might suggest a higher number of employees stop purchasing monthly passes. However, the use value cumulative distribution function from Figure 5-26 suggests that many employees continue purchasing Monthly Passes through Perq despite low ridership. This is likely due to the subsidies offered in Perq. All employees benefit from a pre-tax payroll deduction, which is around a 25-35% discount, and some employees receive additional subsidies from their employer. Taken together, the cost to the employee for a Monthly Pass could be less than half the retail value. With the convenience of having a zero marginal cost pass that auto-renews, the Monthly Pass is often still a worthwhile purchase even with low ridership.

For the remaining full-time employees, many of them are expected to use another mode to commute to work. Around the end of 2020, vehicle miles traveled (VMT) was only about 10-15% lower than a year prior, while bus and subway ridership were 50-80% lower than a year prior. While it is unclear how many people shifted from transit to driving, some employers began offering free

parking during the pandemic and congestion, especially during the peak hours, were greatly reduced. Free or reduced parking costs and less congested streets are likely to have shifted transit users to driving. Additionally, as many people were working remotely throughout the pandemic, there was an increase in cycling trips to be outdoors longer and exercise on the commute. It is unclear how many people shifted from transit to cycling or driving, or if they will return to transit as vaccine distribution increases. Nonetheless, this analysis assumes a portion of employees shift to a different mode. To estimate this, each scenario (except the Full Return scenario) assumes a portion of full-time employees switch and stick to commuting by another mode besides transit. The High Return scenario assumes only 10% of full-time employees leave the Perq system. The Moderate Return scenario assumes 20% of full-time employees leave Perq and the Low Return scenario assumes 30% no longer purchase a pass.

Now that the ridership for each scenario is estimated, the same Mobility Pass growth analysis as from Subsection 5.5.4 is applied. As a reminder, the growth estimate uses data from the MIT Pilot to estimate which groups of employees were most likely to increase their usage (see *Table 5-11*). The MIT Pilot and prior Mobility Pass analyses used fares from before the July 2019 fare increase. Adjusting for the fare increase, new employees at a company are assumed to use an average of \$14.55 more on the MBTA under a Mobility Pass and returning employees who did not previously have a monthly pass use an average of \$5.04 more on the MBTA. Additionally, employee churn was around 30% at MIT; however, given that MIT is a university with post-docs who only stay for a few years, it is assumed that other companies have a 25% churn rate every two years. Applying these values to all non-passholders at their respective companies gets the estimated ridership growth from the Mobility Pass.

Table 5-11: Shift in weekly transit trips from MIT Pilot converted to monthly use value, adjusted for July 2019 fare increase

	Difference	Weekly Trips (x2)	Monthly Trips (x 4.3)	Monthly Use Value (x \$2.40)
All Employees	0.29	0.59	2.52	6.06
No T-Pass	0.24	0.49	2.10	5.04
T-Pass	-0.13	-0.26	-1.10	-2.63
Left/New	0.70	1.41	6.06	14.55

As many employees are assumed to leave Perq because of either reduced ridership or from switching modes, they become ideal candidates to benefit from a Mobility Pass. The fewer employees who return to Perq in the short term, the more effective a Mobility Pass would be at attracting employees back to transit, as well as attracting new riders to transit. This will be illustrated later in this section where the Low Return scenario will have a greater Mobility Pass potential growth (compared to a future without the Mobility Pass) than the High Return scenario, since fewer people would have returned to transit and would be incentivized to take transit with a zero marginal cost pass.

Estimating the number of non-passholders at each employer requires knowing how many employees are at the company and how many passes they use. The number of employees is taken from the May 2019 Corporate Program Survey (CPS), which had a response rate of 25% of Perq employers. The number of passes is known from the MBTA database. However, since only 25% of the employers responded to the survey, the analysis has to be scaled up to the overall Perq population. This process is the same as in Subsection 5.5.5. The revenue generated for each employer based on size is scaled from the survey sample to the Perq population, excluding third-party administrators (such as

WageWorks and Edenred). These values are then scaled a second time assuming that the third-party administrators have similar employer size distributions as Perq.

Finally, it is unlikely that every employer would switch to a Mobility Pass. In the short term, the employers would benefit from a Mobility Pass as ridership would remain low, especially if they are still partially working remotely. Over time, the MBTA would benefit from employers in the Mobility Pass as all employees would be given free additional transit trips (so long as the universality condition is met). However, the Mobility Pass should require at least a 75% subsidy from employers and since only a quarter of employers offer some subsidy for transit it is unlikely that all employers would switch to the Mobility Pass. Thus, this analysis considers the ridership and revenue implications if 25%, 50%, 75%, or all companies enroll in the Mobility Pass. Since employer size has significant implications on ridership and revenue, the proportion of employers who enroll in the Mobility Pass is evenly divided for each company size grouping. For example, for the 25% enrollment rate, this analysis assumes 25% of companies with fewer than 10 cards enroll in the Mobility Pass as do 25% of the companies with over 1000 cards. Since it is unclear which employers would be most likely to enroll in the Mobility Pass, the enrollment of companies is randomized.

The first scenario (Full Return) estimates ridership to return 100% to pre-pandemic levels. This scenario does not assume any changes in company work-from-home policies. If all employers switched to the Mobility Pass, there would be an additional 629,000 new trips in the Full Return scenario. This would be a 32.8% increase in bus and subway trips in Perq. In the second scenario (High Return), ridership is estimated to be at 79% of 2019 levels. This is the second-most optimistic scenario that assumes fully remote work coming from the smallest employers under 25 cards, partial remote work reducing ridership by 30%, and 10% of the remaining employees leaving Perq for an alternate mode (see Table 5-10 for an overview of the scenarios). If all employers switched to the Mobility Pass, using these assumptions, there would be an estimated 647,000 new trips on bus and subway, or a 43.6% increase. *Table 5-12* shows the breakdown of ridership estimates by scenario, company size, and the proportion of companies that enroll in the Mobility Pass. Some employers have greater ridership potential than others depending on the number of non-passholders at the company. For comparisons across employer sizes, assume 100% of employers are enrolling in the Mobility Pass. Note that the two largest employer groups also account for the vast majority of additional trips irrespective of enrollment rate and scenario. This highlights the importance of the largest employers in Perq for ridership growth and revenue potential.

Table 5-12: Ridership estimates by scenario and company size and ridership growth estimated from the Mobility Pass

		Baseline Scenario Ridership Estimates	New Ridership Estimates	Percent Ridership Growth	New Ridership Estimates	Percent Ridership Growth	New Ridership Estimates	Percent Ridership Growth	New Ridership Estimates	Percent Ridership Growth
			25% of companies enroll	50% of companies enroll	75% of companies enroll	100% of companies enroll				
Full Return	< 10 cards	117,657	9,713	8.3%	18,098	15.4%	33,905	28.8%	42,520	36.1%
	10 - 25 cards	156,220	6,098	3.9%	11,006	7.0%	40,717	26.1%	51,872	33.2%
	25 - 50 cards	147,748	13,531	9.2%	6,636	4.5%	28,521	19.3%	30,515	20.7%
	50 - 100 cards	169,125	7,152	4.2%	6,514	3.9%	19,585	11.6%	22,256	13.2%
	100 - 1000 cards	390,641	23,132	5.9%	93,909	24.0%	127,284	32.6%	136,235	34.9%
	Over 1000 cards	935,489	109,890	11.7%	264,993	28.3%	267,282	28.6%	345,636	36.9%
	Total	1,916,880	169,516	8.8%	401,155	20.9%	517,294	27.0%	629,034	32.8%
High Return	< 10 cards	44,613	4,211	9.4%	11,458	25.7%	19,530	43.8%	24,414	54.7%
	10 - 25 cards	84,376	6,013	7.1%	10,342	12.3%	37,380	44.3%	47,778	56.6%
	25 - 50 cards	123,245	13,875	11.3%	8,224	6.7%	31,865	25.9%	34,299	27.8%
	50 - 100 cards	138,936	7,856	5.7%	8,472	6.1%	22,140	15.9%	25,617	18.4%
	100 - 1000 cards	324,435	26,311	8.1%	100,004	30.8%	137,044	42.2%	146,811	45.3%
	Over 1000 cards	769,026	121,741	15.8%	280,370	36.5%	284,130	36.9%	368,299	47.9%
	Total	1,484,631	180,008	12.1%	418,868	28.2%	532,089	35.8%	647,218	43.6%
Moderate Return	< 10 cards	51,065	7,480	14.6%	11,943	23.4%	20,154	39.5%	26,585	52.1%
	10 - 25 cards	88,554	2,801	3.2%	10,894	12.3%	41,978	47.4%	49,012	55.3%
	25 - 50 cards	58,898	223	0.4%	5,739	9.7%	14,338	24.3%	14,560	24.7%
	50 - 100 cards	118,937	8,927	7.5%	10,230	8.6%	24,594	20.7%	29,177	24.5%
	100 - 1000 cards	276,925	29,512	10.7%	106,034	38.3%	146,739	53.0%	157,344	56.8%
	Over 1000 cards	651,497	133,294	20.5%	294,961	45.3%	300,348	46.1%	389,906	59.8%
	Total	1,245,875	182,237	14.6%	439,801	35.3%	548,151	44.0%	666,586	53.5%
Low Return	< 10 cards	60,672	10,418	17.2%	20,858	34.4%	35,551	58.6%	45,116	74.4%
	10 - 25 cards	84,920	7,840	9.2%	14,661	17.3%	46,913	55.2%	58,653	69.1%
	25 - 50 cards	63,167	6,020	9.5%	9,601	15.2%	20,905	33.1%	22,971	36.4%
	50 - 100 cards	24,529	5,391	22.0%	8,183	33.4%	13,574	55.3%	13,574	55.3%
	100 - 1000 cards	234,011	31,880	13.6%	111,893	47.8%	157,075	67.1%	168,538	72.0%
	Over 1000 cards	563,817	143,268	25.4%	309,357	54.9%	315,178	55.9%	410,394	72.8%
	Total	1,031,117	204,817	19.9%	474,554	46.0%	589,196	57.1%	719,246	69.8%

However, ridership at 79% of pre-pandemic levels is not expected for the next few years. As previously mentioned, the MBTA anticipates, at best, 89% of fare revenue from pre-pandemic levels by Fiscal Year 2024. Instead, and especially over the next few years, the Moderate and Low Return scenarios are likely to reflect Perq ridership levels. The Moderate Return scenario would be roughly 66% of pre-pandemic ridership while the Low Return scenario would only be 54% of pre-pandemic ridership. In the Moderate Return scenario, there would be roughly 666,600 new trips on bus and subway, which would be a 53.5% increase from the baseline. In the Low Return scenario (assuming 100% enrollment), an estimated 719,000 new bus and subway trips would occur, which would increase ridership by almost 70%. It is important to note that the lower ridership on the system, the greater potential for new ridership under a Mobility Pass. This is true across all enrollment scenarios and company sizes. The reason for the highest ridership gains in the lowest ridership return scenario is because a Mobility Pass would attract more users. The number of employees on transit is at its lowest in the fourth scenario, so the non-passholders (and potential ridership growth) is highest in this scenario. This further emphasizes the importance of implementing the Mobility Pass early in the post-pandemic recovery process.

While ridership will grow regardless of scenario or enrollment rate, the revenue varies. Table 5-13 and Table 5-14 show the baseline revenue by scenario and employer size as well as the estimated change in revenue from a Mobility Pass based on the enrollment rate. Table 5-13 shows the revenue estimates for a 25% and 50% enrollment rate while Table 5-14 shows the revenue estimates for a 75% and 100% enrollment rate. Note that revenue from the Mobility Pass fluctuates by employer size, enrollment rates, and scenario. Some employers will yield a positive revenue when switching to the Mobility Pass while others would result in less revenue than the counterfactual. However, if all

employers were to switch to the Mobility Pass, then there would be a net positive revenue gain, irrespective of scenario. The variation in revenue is based on the employers that were randomly selected for each enrollment rate.

Table 5-13: Revenue estimates by scenario and company size and revenue changes under a Mobility Pass assuming 25% and 50% enrollment

		Baseline Scenario Revenue	Revenue from Mobility	Revenue if no Mobility	Change in Revenue	Revenue from Mobility	Revenue if no Mobility	Change in Revenue	
		25% of companies enroll				50% of companies enroll			
Full Return	< 10 cards	\$ 329,601	\$ 95,809	\$ 88,885	\$ 6,924	\$ 183,545	\$ 163,329	\$ 20,216	
	10 - 25 cards	\$ 456,993	\$ 79,498	\$ 75,772	\$ 3,726	\$ 229,644	\$ 237,184	\$ (7,540)	
	25 - 50 cards	\$ 434,139	\$ 84,612	\$ 64,891	\$ 19,721	\$ 156,618	\$ 174,656	\$ (18,037)	
	50 - 100 cards	\$ 471,116	\$ 160,192	\$ 139,389	\$ 20,803	\$ 191,142	\$ 229,216	\$ (38,074)	
	100 - 1000 cards	\$ 1,175,866	\$ 362,969	\$ 371,365	\$ (8,397)	\$ 826,706	\$ 764,292	\$ 62,415	
	Over 1000 cards	\$ 2,937,165	\$ 1,487,630	\$ 1,498,535	\$ (10,905)	\$ 2,250,976	\$ 2,044,794	\$ 206,182	
	Total	\$ 5,804,879	\$ 2,270,709	\$ 2,238,837	\$ 31,872	\$ 3,838,632	\$ 3,613,470	\$ 225,162	
High Return	< 10 cards	\$ 130,735	\$ 33,021	\$ 28,122	\$ 4,900	\$ 79,133	\$ 61,833	\$ 17,300	
	10 - 25 cards	\$ 265,122	\$ 51,048	\$ 50,966	\$ 82	\$ 144,324	\$ 154,080	\$ (9,755)	
	25 - 50 cards	\$ 382,889	\$ 77,490	\$ 57,878	\$ 19,611	\$ 135,048	\$ 151,868	\$ (16,820)	
	50 - 100 cards	\$ 418,724	\$ 136,653	\$ 127,099	\$ 9,554	\$ 160,924	\$ 198,330	\$ (37,406)	
	100 - 1000 cards	\$ 1,051,475	\$ 311,566	\$ 330,362	\$ (18,796)	\$ 738,202	\$ 685,393	\$ 52,809	
	Over 1000 cards	\$ 2,584,833	\$ 1,299,491	\$ 1,317,311	\$ (17,820)	\$ 2,003,481	\$ 1,800,632	\$ 202,849	
Total	\$ 4,833,776	\$ 1,909,270	\$ 1,911,739	\$ (2,469)	\$ 3,261,113	\$ 3,052,136	\$ 208,977		
Moderate Return	< 10 cards	\$ 155,077	\$ 52,881	\$ 43,898	\$ 8,983	\$ 93,117	\$ 81,051	\$ 12,066	
	10 - 25 cards	\$ 282,115	\$ 42,809	\$ 43,645	\$ (836)	\$ 135,759	\$ 138,787	\$ (3,028)	
	25 - 50 cards	\$ 191,841	\$ 8,440	\$ 12,516	\$ (4,076)	\$ 72,282	\$ 80,804	\$ (8,522)	
	50 - 100 cards	\$ 363,690	\$ 117,110	\$ 103,167	\$ 13,942	\$ 149,690	\$ 175,691	\$ (26,002)	
	100 - 1000 cards	\$ 914,819	\$ 288,944	\$ 283,632	\$ 5,312	\$ 684,728	\$ 594,961	\$ 89,768	
	Over 1000 cards	\$ 2,246,571	\$ 1,164,248	\$ 1,135,486	\$ 28,762	\$ 1,832,369	\$ 1,566,464	\$ 265,905	
Total	\$ 4,154,113	\$ 1,674,431	\$ 1,622,344	\$ 52,087	\$ 2,967,945	\$ 2,637,758	\$ 330,187		
Low Return	< 10 cards	\$ 179,591	\$ 61,051	\$ 50,739	\$ 10,312	\$ 129,716	\$ 96,586	\$ 33,130	
	10 - 25 cards	\$ 269,493	\$ 51,445	\$ 41,206	\$ 10,239	\$ 146,977	\$ 140,238	\$ 6,738	
	25 - 50 cards	\$ 203,592	\$ 36,904	\$ 29,943	\$ 6,961	\$ 97,226	\$ 98,280	\$ (1,054)	
	50 - 100 cards	\$ 86,754	\$ 39,589	\$ 41,235	\$ (1,646)	\$ 54,018	\$ 45,520	\$ 8,498	
	100 - 1000 cards	\$ 780,114	\$ 271,540	\$ 259,942	\$ 11,598	\$ 642,461	\$ 523,504	\$ 118,957	
	Over 1000 cards	\$ 1,946,747	\$ 1,089,062	\$ 1,000,507	\$ 88,555	\$ 1,714,324	\$ 1,347,227	\$ 367,097	
Total	\$ 3,466,292	\$ 1,549,590	\$ 1,423,571	\$ 126,019	\$ 2,784,721	\$ 2,251,355	\$ 533,365		

In the Full Return scenario, the Mobility Pass would increase monthly revenue by \$305,000 if all employers enrolled. However, the variability in revenue change could be as low as a \$32,000 gain to \$384,500, depending on which employers enroll in the Mobility Pass. The revenue implications suggest a positive benefit from the Mobility Pass as ridership would increase significantly with minimal revenue risks and the potential for greater revenue boosts. Variability changes across each scenario, as the High Return scenario could lose \$2,500 a month or gain \$355,000. In the Moderate and Low Return scenarios, the benefits are even greater. In the Moderate Return scenario, the lower bound of revenue change would be a \$52,000 revenue boost while the MBTA could see a revenue growth of nearly \$460,000 per month. The potential revenue growth is over 10% of the expected revenue in the Moderate Return scenario. In the Low Return scenario, revenue is positive regardless of enrollment rate. This might not always be the case, as some scenarios might show lower revenue. Regardless, the lower bound of revenue is at least an additional \$126,000 per month and could be as high as \$737,000 per month. That revenue growth would be 20% of the baseline scenario revenue.

As aforementioned, the Mobility Pass has greater benefits with lower expected ridership returns as it would increase the number of employees who would benefit from a pass-like product. As many people may be hesitant to purchase a monthly pass due to their low ridership, a Mobility Pass would automatically offer them that benefit, making transit more enticing compared to other modes.

Table 5-14: Revenue estimates by scenario and company size and revenue changes under a Mobility Pass assuming 75% and 100% enrollment

		Baseline Scenario Revenue	Revenue from Mobility	Revenue if no Mobility	Change in Revenue	Revenue from Mobility	Revenue if no Mobility	Change in Revenue
		75% of companies enroll				100% of companies enroll		
Full Return	< 10 cards	\$ 329,601	\$ 289,013	\$ 240,459	\$ 48,554	\$ 384,424	\$ 329,601	\$ 54,823
	10 - 25 cards	\$ 456,993	\$ 365,845	\$ 327,781	\$ 38,064	\$ 499,421	\$ 456,993	\$ 42,428
	25 - 50 cards	\$ 434,139	\$ 374,057	\$ 370,102	\$ 3,955	\$ 427,831	\$ 434,139	\$ (6,308)
	50 - 100 cards	\$ 471,116	\$ 317,846	\$ 316,042	\$ 1,805	\$ 459,315	\$ 471,116	\$ (11,801)
	100 - 1000 cards	\$ 1,175,866	\$ 1,180,524	\$ 1,067,786	\$ 112,737	\$ 1,264,593	\$ 1,175,866	\$ 88,727
	Over 1000 cards	\$ 2,937,165	\$ 2,342,213	\$ 2,162,815	\$ 179,398	\$ 3,074,701	\$ 2,937,165	\$ 137,536
	Total	\$ 5,804,879	\$ 4,869,498	\$ 4,484,985	\$ 384,513	\$ 6,110,284	\$ 5,804,879	\$ 305,404
High Return	< 10 cards	\$ 130,735	\$ 122,987	\$ 91,804	\$ 31,183	\$ 165,666	\$ 130,735	\$ 34,932
	10 - 25 cards	\$ 265,122	\$ 224,855	\$ 178,490	\$ 46,365	\$ 317,169	\$ 265,122	\$ 52,047
	25 - 50 cards	\$ 382,889	\$ 329,842	\$ 324,502	\$ 5,340	\$ 378,105	\$ 382,889	\$ (4,784)
	50 - 100 cards	\$ 418,724	\$ 272,904	\$ 279,173	\$ (6,269)	\$ 394,927	\$ 418,724	\$ (23,797)
	100 - 1000 cards	\$ 1,051,475	\$ 1,055,520	\$ 954,711	\$ 100,809	\$ 1,130,991	\$ 1,051,475	\$ 79,516
	Over 1000 cards	\$ 2,584,833	\$ 2,080,532	\$ 1,902,864	\$ 177,668	\$ 2,729,581	\$ 2,584,833	\$ 144,748
	Total	\$ 4,833,776	\$ 4,086,640	\$ 3,731,544	\$ 355,096	\$ 5,116,438	\$ 4,833,776	\$ 282,662
Moderate Return	< 10 cards	\$ 155,077	\$ 138,422	\$ 111,440	\$ 26,982	\$ 186,362	\$ 155,077	\$ 31,284
	10 - 25 cards	\$ 282,115	\$ 264,116	\$ 215,840	\$ 48,276	\$ 330,158	\$ 282,115	\$ 48,044
	25 - 50 cards	\$ 191,841	\$ 167,860	\$ 179,326	\$ (11,466)	\$ 176,300	\$ 191,841	\$ (15,541)
	50 - 100 cards	\$ 363,690	\$ 253,541	\$ 250,821	\$ 2,720	\$ 355,474	\$ 363,690	\$ (8,216)
	100 - 1000 cards	\$ 914,819	\$ 972,986	\$ 830,982	\$ 142,004	\$ 1,042,246	\$ 914,819	\$ 127,427
	Over 1000 cards	\$ 2,246,571	\$ 1,898,943	\$ 1,647,902	\$ 251,041	\$ 2,499,367	\$ 2,246,571	\$ 252,796
	Total	\$ 4,154,113	\$ 3,695,868	\$ 3,236,311	\$ 459,558	\$ 4,589,907	\$ 4,154,113	\$ 435,794
Low Return	< 10 cards	\$ 179,591	\$ 192,382	\$ 126,984	\$ 65,398	\$ 253,890	\$ 179,591	\$ 74,300
	10 - 25 cards	\$ 269,493	\$ 261,081	\$ 195,905	\$ 65,176	\$ 344,576	\$ 269,493	\$ 75,083
	25 - 50 cards	\$ 203,592	\$ 185,127	\$ 180,238	\$ 4,889	\$ 206,731	\$ 203,592	\$ 3,139
	50 - 100 cards	\$ 86,754	\$ 93,607	\$ 86,754	\$ 6,853	\$ 93,607	\$ 86,754	\$ 6,853
	100 - 1000 cards	\$ 780,114	\$ 900,755	\$ 705,820	\$ 194,935	\$ 966,119	\$ 780,114	\$ 186,006
	Over 1000 cards	\$ 1,946,747	\$ 1,785,249	\$ 1,439,111	\$ 346,138	\$ 2,338,108	\$ 1,946,747	\$ 391,361
	Total	\$ 3,466,292	\$ 3,418,201	\$ 2,734,812	\$ 683,388	\$ 4,203,032	\$ 3,466,292	\$ 736,741

The Mobility Pass is an efficient method to increasing ridership across employers by reducing the cost (and ticket purchase transaction) barriers to riding transit. With reduced ridership expected on the MBTA over at least the next five years, it is especially critical to incentivize ridership early in the recovery to get riders in the habit of taking transit rather than an alternative. The Mobility Pass would increase ridership by around 170,000 to 719,000 additional monthly linked trips, depending on enrollment rate and ridership return scenario. Additionally, revenue would, at worst⁹, decrease by \$2,500 per month but has the potential to be as high as \$737,000 per month and is more likely to be positive than negative. Shifting employees onto transit early on could potentially continue to increase ridership as time passes, as was shown in the MIT Pilot prior to the pandemic.

⁹ Note that the analysis used random generators for which employers to enroll and which employees to leave the system. A redraw of those randomly generated employers and employees might yield different results.

While there are still many unknowns in regards to pandemic recovery and ridership growth, a Mobility Pass would help increase ridership and could potentially snowball into higher ridership than expected. With new work-from-home policies that will likely reduce the number of trips employees take to the office, a Mobility Pass would provide a zero marginal cost pass that would encourage those hesitant to purchase a monthly pass (due to reduced travel) to ride transit. The inherent flexibility offered by a Mobility Pass is ideal for a post-pandemic period that will likely retain remote work flexibility. Additionally, many employees who previously had to purchase individual tickets would now benefit from a pass, further reducing the cost barrier.

5.8 Mobility Pass Potential and Implications

The Mobility Pass was first piloted at MIT in 2016 as a way to increase ridership by decreasing the individual price of transit at a cheaper cost for the employer. Before the pandemic, the Mobility Pass would have increased ridership but possibly at a small cost to the MBTA, depending on which companies adopted the new pass. However, COVID-19 has temporarily, and possibly permanently impacted the ways in which people commute. Most notably, work-from-home increased dramatically during the pandemic which is partially responsible for the reduced Perq ridership of about 75-80%. The Mobility Pass has, therefore, emerged as a way to attract ridership to transit post-pandemic. In fact, the Mobility Pass is estimated to add anywhere from 170,000 to 719,000 new monthly trips and could increase monthly revenue by \$737,000, if all employers were to enroll. Those increases do not account for year-over-year growth as was found at MIT in the years following the pilot.

There are many factors contributing to the heavily reduced Perq ridership. For one, many employees have been working remotely since the first stay-at-home order in March 2020. For the employers who have remained in-person, some have reduced parking costs, or even made parking free, as was the case at MIT. Additionally, peak hour travel has decreased significantly, which has reduced congestion levels on the roads. Less congestion and cheap parking are likely contributing to employees driving to work who previously took transit. Other modes have seen growth since the pandemic began, such as cycling. Regaining transit ridership will be a challenge for the MBTA over the next few years. One way to expediting that recovery would be by offering a Mobility Pass for employers beyond just the MIT pilot.

The MBTA should also create promotional material for employers on the benefits they would receive on a Mobility Pass. For example, MIT spent one-third of what it would have otherwise paid in order to provide free transit to all employees. That is a major benefit at a heavily reduced cost to the employer. In addition, the MBTA (using data it has on individual employers) should target which employers would be ideal for a Mobility Pass. This would primarily be employers with a relatively low share of passholders. Those employers would have large potential gains in ridership from non-passholder employees. The Mobility Pass should be available to all employers, but the MBTA should target which employers they encourage to join the Mobility Pass.

While this analysis focuses on local bus and subway trips, the Mobility Pass could also be applied to commuter rail. The Fiscal Management and Control Board for the MBTA has recently been pushing for a regional rail transformation of the commuter rail system. This vision, which could take decades to complete, aims to reduce commuter rail headways to 15 to 20 minutes and provide all-day service. Currently, commuter rail operates low frequencies, especially off-peak, with many stations receiving less than one train per hour in the off-peak. A significant increase in frequency, as is proposed, would provide increased flexibility for commuter rail passengers. A Mobility Pass for commuter rail

would likely pair nicely with this increased frequency as it would offer increased flexibility to employees.

Additionally, the MBTA is in the process of implementing their new fare collection system, known as AFC 2.0. The new fare system would include the ability for the MBTA to adopt fare capping. Fare capping is where trips are purchased individually, as pay-as-you-go or stored value, but are limited to a weekly or monthly cap. Once the cap is reached, every additional trip is free for the user for the rest of the period. Fare capping would remove many of the financial benefits of monthly passes for the MBTA as underutilized passes no longer provide the full cost of the pass. As mentioned in Section 5.6.3, around 70% of Perq users did not reach the pass multiple for a monthly LinkPass. In the current fare structure, those users (either directly or subsidized through their employer) still purchased the full cost of the pass. Under a fare capping fare structure, those users would have given the MBTA less in revenue as they would not have reached the cap. A Mobility Pass, however, is structured similarly to a fare cap where the trips are paid on a pay-as-you-go basis. The benefit of the Mobility Pass is the zero marginal cost to the employee, which is similar to a monthly pass. Thus, a Mobility Pass would be even more effective under fare capping as it would have the benefits of a pass product.

Chapter 6: Conclusion

The COVID-19 pandemic has drastically reduced transit ridership, especially among commuter rail and traditional 9 to 5 workers. Research from other studies as well as from the December 2020 Employer Panel Survey from this research suggests that many employers will continue some level of work-from-home policies as travel restrictions are lifted (Bartik et al., 2020). This research examined three potential methods to increasing ridership on the MBTA specifically through fare products. There are other ways the MBTA could attract ridership back to its system, such as increasing frequency of service, improving reliability, and redesigning bus routes to better match rider travel patterns. This research focuses solely on attracting new and returning ridership through new fare products and marketing campaigns.

6.1 Overview

The COVID-19 pandemic drastically reduced ridership on transit. Ridership on the MBTA decreased by 80-95% immediately following the first stay-at-home order. Throughout 2020 and early 2021, ridership never managed to surpass 50% on any one mode. On top of drastic reductions in ridership during the pandemic, ridership was already decreasing before the pandemic. This is due in part to increased competition from Transportation Network Companies (TNCs) such as Uber and Lyft, from poor service reliability and frequency, and from multiple fare hikes in the past decade. Thus, the importance of attracting ridership back to the MBTA was important before the pandemic even began. This research describes the pre-pandemic ridership trends, analyzes the effects of COVID-19 on commuter rail and Perq, and proposes new fare products to quicken the post-pandemic recovery.

6.1.1 Pre-Pandemic Ridership Trends

Before COVID-19, transit agencies had to prioritize ridership and revenue, where ridership was a measure of the social utility provided by transit, which justifies the State subsidy that covers two-thirds of the operating budget, and revenue to cover the remaining third of the operating budget. Across the MBTA system, ridership has been in decline in the five years preceding the pandemic. Subway and commuter rail ridership reached a peak in 2014 (based on unlinked trips) and bus in 2015 and each decreased by 10-14% over the next five years. On commuter rail, however, revenue was increasing despite declining ridership. This was primarily from the fare hikes, which are likely to have influenced, at least partially, continued decreased ridership. Ridership may have also been decreasing from increased competition (i.e. TNCs) and poor service provision. mTicket, which was first introduced at the end of 2012, was increasing in popularity and capturing a larger revenue share each year. Before the pandemic, mTicket accounted for just over a third of all commuter rail revenue.

In Perq, more companies have been joining Perq, but they have mostly been smaller employers. Perq employees and companies are quite inelastic when it comes to fare increases at the MBTA. In fact, revenue and card orders both increased in the three years prior to the pandemic despite a fare increase in July 2019. The discount from Perq (25-35% from pre-tax payroll deductions plus any subsidies from employers) makes employees less susceptible to fare hikes and provides a steady revenue stream for the MBTA. Commuter rail makes up 54% of Perq revenue but only 29% of pass orders. This emphasizes the high cost of commuter rail passes relative to bus and subway passes.

6.1.2 COVID-19 Impacts on Ridership and Revenue

COVID-19 drastically reduced travel across all modes. However, transit has been one of the most impacted modes. Driving only decreased 10-40% in regards to VMT nationwide while the MBTA saw decreases of 50-80% on bus, 60-90% on subway, and around 85-95% on commuter rail. This drop in ridership reduced crowding on most services and routes, which helped minimize the concern of contracting the virus on transit. In addition, the MBTA, in order to keep their operators safe, implemented a rear-door policy on buses and paused fare collection on commuter rail from mid-March to mid-July. This means data collection is minimal during those months. This research uses data from before March 2020 and after July 2020 to ensure an accurate representation of travel behaviors.

Studies show how those who continued traveling during the pandemic were primarily “essential workers” (i.e. healthcare, grocery store workers, delivery, etc.). This corresponded with a higher proportion of minority, women, and low-income riders who took transit during the pandemic. The previous riders who left the system were predominantly white and higher income and worked “non-physical occupations” (Liu et al., 2020). In essence, this meant people who worked in downtown offices shifted to remote work while those who worked at grocery stores or in healthcare continued to commute. The removal of the 9 to 5 commuter had profound impacts on the transit system. Much of the decrease in transit ridership came from these temporary work-from-home policies from downtown office employers. However, out of an overabundance of caution and decreased demand, some employers (such as MIT) implemented free parking policies during much of the pandemic. Discounted or free parking on top of reduced congestion, especially earlier in the pandemic, likely shifted many users away from taking transit, especially for those with the long transit commutes who generally have a vehicle available and used it to access the commuter rail stations.

Using k-means clustering on mTicket users, this research segmented the commuter rail population based on their travel behaviors. Clusters were made for January 2020 as a pre-pandemic baseline and October 2020 as the baseline during the pandemic. The clusters that had the lowest retention of riders were the frequent, occasional, and peak clusters. The weekend and off-peak clusters had, conversely, retained the highest ridership. Users in each cluster also exhibited lower ridership during the pandemic than before, further highlighting the decrease in ridership.

In Perq, monthly pass revenue pre-paid by the employers decreased by around 75-90% on bus and subway and by around 55-90% on commuter rail. The MBTA implemented policies for both bus and subway and commuter rail in an effort to prevent a mass exodus from Perq. Their efforts were successful in slowing the departure from Perq but could not retain the employees who were no longer commuting. However, many hospital systems are enrolled in Perq and provided a steady revenue stream throughout the pandemic.

6.1.3 Strategies at Recovering Ridership

The MBTA does not anticipate a full recovery for at least the next half-decade. A recent presentation to the Fiscal Management and Control Board (FMCB) suggested that fare revenue will remain below pre-pandemic levels at least until the end of Fiscal Year 2026 (O'Hara & Panagore, 2021). Under those assumptions, this research creates ridership return scenarios that are between current ridership levels and pre-pandemic ridership levels, including a scenario that assumes a full return to pre-pandemic ridership. This research proposed new fare products that could attract riders back to the system as quickly as possible. The emergency relief funds from the Federal government,

which provided financial stability to transit agencies, has tended to reinforce the importance of building back ridership.

For commuter rail, the MBTA introduced the Flex Pass in July 2020 as a way to capture the reduced travel commuters. However, it had marginal success, in part due to the low discount (10%) and also from the day-pass requirement. Revenue shares only reached 3% on commuter rail. Additionally, many of the Flex Pass users were previously pay-as-you-go riders rather than Monthly Pass users, and many migrated to PAYG rather than to a Monthly Pass. Instead, this research examines alternate fare product designs for the Flex Pass and introduces two new fare products: the 20/30 and 30/60 product. The 20/30 and 30/60 offer 20 (or 30) trips within 30 (or 60) days. These are trip-based which is useful as users only took a one-way trip on 65% of days during the pandemic.

The new fare products, and the original Flex Pass, will need to be marketed if the MBTA expects users to switch to them. This research suggests implementing email marketing campaigns to nudge users onto the new pass products, as well as onto the Monthly Pass. The mTicket account-based system and individual employer-based marketing campaigns provides two platforms for sending targeted email messages to potential pass adopters.

For bus and subway, the Perq program could adopt a Mobility Pass for employers. The Mobility Pass has three conditions (not all have to be met, except for universality): universality (all employees are covered), zero marginal cost (each additional trip does not cost more to an individual employee), and heavy subsidy (the employer covers at least 75% of the cost). This product was piloted at MIT with success at increasing ridership and revenue for the MBTA while providing all employees free transit at a significantly reduced cost for MIT. The win-win product could help employers avoid adding parking and increase employee satisfaction while also increasing the recovery rate on transit.

6.2 Key Findings

Based on the cluster analysis on commuter rail, the Multi-day Frequent cluster had the sharpest ridership decline at 95%, while the Weekend clusters only saw around a 45-55% decrease in ridership. Peak clusters were most likely to experience ridership declines, as were the more frequent clusters. These are important for the MBTA to know as they look to recapture ridership. New fare products should be geared towards attracting these users back to the system. Additionally, nearly half of mTicket users during the pandemic were new to mTicket since the first stay-at-home orders in March 2020. This suggests that many commuter rail riders adopted mTicket during the pandemic, potentially as a safety precaution.

The Flex Pass has only captured around 3% of mTicket fare revenue. Despite offering a discount, most commuter rail riders still preferred using PAYG tickets. To counteract that, a deeper discount on Flex Pass could see increased ridership. On top of that, a 20/30 or 30/60 fare product would see increases in ridership of around 15,000 more trips per month and around a 1.5-percentage point increase in the market share than a similarly discounted Flex Pass.

Two randomized controlled trials (RCTs) conducted before the pandemic showed that email nudging could be used as a tactic to increase product adoption rates. The Monthly Pass Campaign separated PAYG users into four categories based on their usage and saw an increase among Near and Consistent Recent groups, especially from those who opened the email. However, an increase in pass purchases were found across all four groups (even though they were not all statistically significant). The Leisure Campaign saw modest results of Weekend Pass purchases, especially earlier

in the Fall. As the weather worsened, the marketing campaign did not appear to nudge people to the Weekend Pass. Nonetheless, using an email marketing campaign can nudge people into these new products during the ridership return.

Finally, the Mobility Pass would have significant benefits to both ridership and revenue but depends on the enrollment rate from employers. However, even at lower enrollment rates, the Mobility Pass would increase ridership by around 170,000 trips per month. With full adoption, there would be upwards of 720,000 new trips per month on the Mobility Pass. Revenue is not expected to drop by more than \$2,500 per month, which is minimal compared to the \$2 Million per month they currently generate. On the flip side, the MBTA could increase revenue by roughly \$737,000 per month if all employers adopted the Mobility Pass. Additionally, the Mobility Pass has greater benefits if implemented earlier on as the universality condition would expand the number of employees who would benefit from reduced transit with zero marginal cost.

6.3 Recommendations

First, the MBTA should implement the 20/30 fare product on commuter rail. There is a lot of overlap between the 20/30 and 30/60 products. In fact, 96% of users who would benefit from a 30/60 product would also benefit from a 20/30 product. On top of that, there is an additional 15% of users who would benefit from a 20/30 but not a 30/60 product. In regards to the discount rate, a 20% discount is ideal as it would be most effective at drawing back ridership to the system. However, to keep the Monthly Pass as the ideal frequent-user product, the MBTA should increase the discount on the Monthly Pass to 30% in order to maintain as many monthly passholders as possible and account for the likely continuation of some level of remote work and fewer overall commuters. Additionally, this deeper discount would pair well with the discount from the Perq program, which accounts for 40% of revenue on commuter rail. The 30% discount on the Monthly Pass with the additional 25-35% pre-tax payroll deduction and any subsidies by employers would make the breakeven point for employees be below three workdays of round trip travel per week. Therefore, the 20/30 product at a 20% discount and an increase of the current Monthly Pass discount to 30% is recommended.

To market this product, the MBTA should implement consistent email marketing campaigns that targets users who have ridership behaviors that could benefit from one of the new fare products. This is a relatively cheap method and was shown to increase the purchase rate of Monthly Passes. As marketing will continue to be difficult while many people still work from home, a targeted email campaign can help increase product purchase rates where possible.

For the Perq Program, the Mobility Pass should be made available and marketed to all employers immediately. The minimum subsidy requirement by employers should be set to 75% to ensure deep discounts for employees. Universality should also be a requirement so non-passholders are incentivized to take transit. The revenue risk from offering a Mobility Pass is minimal compared to the additional ridership that would be captured. Additionally, there is a good chance that the MBTA would actually increase their revenue from a Mobility Pass given the reduced travel that is anticipated post-pandemic. To get employers on the Mobility Pass, the MBTA should develop promotional material based on the success of the MIT pilot and the benefits to employers and employees.

Finally, the MBTA should look into expanding the 20/30 and 30/60 fare products to the bus and subway system and look into making the Mobility Pass available for commuter rail as well. While

this research focused on commuter rail for the 20/30 and 30/60 products, they could also be applied on the bus and subway system. However, research should be done to examine the adoption rates of these products and the ideal discount. The Mobility Pass is capable of being implemented on commuter rail, especially with mTicket. The MBTA should look into the implications of expanding the Mobility Pass onto commuter rail.

The above recommendations are primarily focused with fare product adoption marketing. However, given the drastic decrease in fare revenue during the pandemic, there should be a serious discussion about the reliance of transit agencies on fare revenue. States and regional authorities often look at farebox recovery ratios when considering which agencies should get capital or additional operations funding. The farebox recovery ratio, or the proportion of the operations budget that is covered by the fares, is not an ideal method of judging the efficiency of a transit agency. For starters, very few if any transit agencies ever take more in fares than they expend in operations expenses.

The farebox recovery ratio sends mixed signals as well. In fact, the pressure to increase the farebox recovery ratio is part of the rationale to the numerous fare hikes on the MBTA. The MBTA has increased fares in 2012, 2014, 2016, and 2019 in an effort to reduce debt and increase the farebox recovery ratio. However, increasing fares leads to a decrease of ridership. This is becoming increasingly true on commuter rail, where a Zone 5 fare cost \$6.25 prior to the 2012 fare increase and now costs \$9.75 after the 2019 fare hike. That is over a 50% increase in the fare in less than a decade. In response, commuter rail ridership was in decline prior to the COVID-19 pandemic. Thus, pursuing an increase in the farebox recovery ratio is at odds with providing transportation access to all residents. To best avoid a future fiscal crisis for the MBTA, there should be serious discussions about shifting away from the farebox recovery ratio. The revenue would have to come from another source. That source, however, should be resilient to future crises, whether they be another global pandemic or some other external disaster.

6.4 Future Research

As aforementioned, one potential direction for future research is to look at expanding the 20/30 and 30/60 products to the bus and subway system and the Mobility Pass to the commuter rail system. The new AFC 2.0 fare system will integrate fare collection across the bus, subway, and commuter rail systems, which would further benefit adding the 20/30 and 30/60 products on bus and subway and the Mobility Pass onto commuter rail. Additionally, an account-based system, as AFC 2.0 is intended to become, will make email marketing easier to implement. Therefore, advertising new products on bus and subway would be made easier under AFC 2.0. New RCTs could be executed under AFC 2.0 on bus and subway as well.

A regional rail system of all-day frequent service would also make a Mobility Pass for commuter rail more attractive. Currently, ridership on commuter rail is primarily during the peak hours as frequency drops significantly in the off-peak. Under all-day frequent service, people would be able to travel to and from their homes more often, increasing the number of trips in the off-peak. A Mobility Pass for commuter rail would further encourage off-peak travel as it decreases the cost to the passenger and provides employer-subsidized incremental revenue to the MBTA at the same time. Exploring the benefits of regional rail and matching fare products to it is another future research direction.

Finally, the new AFC 2.0 system has the potential of switching to a “capped” period-based fare structure. That would have significant impacts on fare products and revenue across the MBTA

system. Future research could examine the potential benefits and risks of switching to a fare capping structure. Additionally, Perq would lose many of its benefits if fare capping were introduced, as nearly three-quarters of ridership did not reach the pass multiple. Thus, a Mobility Pass would likely be even more attractive under this structure as it would be available to all benefits-eligible employees at a company. Future research could consider the impacts of fare capping on the MBTA system as well as the Perq program.

Appendix A: K-Means Clustering Methodology

The purpose of this analysis is to segment customers by similar travel behaviors to see how these users differed in responses to the pandemic. There are many different ways to classify customers into segments. Historically, many transit agencies use a rule-based approach that segments users by the number of trips taken (i.e. more or less than 20 trips per month) or by their temporal usage (i.e. over 50% of their trips during the peak hour). While this is a straightforward way to cluster users, it requires a priori knowledge of what the threshold values should be set at. Instead, this analysis uses contemporary clustering approaches using machine learning, specifically k-means clustering. Machine learning clustering algorithms find similarities in the data points (each data point is a user, in this case) and clusters them based on those similarities. This can find patterns that might not be easy to identify from a priori knowledge or familiarity with the data set.

Two time periods are analyzed to compare pre-COVID-19 ridership to ridership during the pandemic. The pre-pandemic period is the month of January in 2020. A full month was used to match with the Monthly Pass product, which is primarily used by the most frequent passengers. October 2020 was used as the example month during the pandemic. The MBTA was not formally collecting fares between the end of March and July 2020 for safety precautions, so no ridership data is available during that period. At the end of July 2020, fare collection resumed and the data was available again. Ridership was slowly increasing between August and September and plateaued around October, making it an ideal month to analyze ridership during the pandemic.

A.1 K-Means Clustering Overview

K-means is an unsupervised machine learning algorithm that is used to classify data points into clusters. These clusters are based on the Euclidean distance of each data point to other data points. K-means is a simple algorithm that is computationally fast, which is useful with hundreds of thousands of data points, as are used in this analysis. There are other potential clustering algorithms, such as fuzzy c-means, DBSCAN, Gaussian Mixture Model, hierarchical clustering, etc. This analysis uses k-means for its quick computation and simple application while still providing a robust clustering method.

The initiation of k-means begins with k centroids randomly placed in the dataset. Each data point in the set is assigned to the nearest centroid. When each point is classified by the nearest centroid, the centroid is recalculated for each cluster group. This will shift the centroids towards a local optimum of the centroid location. This process is repeated by again assigning each data point to the nearest centroid and then recalculating the centroid for each cluster. After the data points no longer change clusters and the centroids are the same, the assignment is set.

There are components that must be determined before applying k-means clustering. The first is the feature set. The feature set are the variables that are included in the analysis. The second is the hyperparameter, k , which indicates the number of clusters. While these two components are chosen by the analyst, there are algorithms that help the analyst find optimal variables and values. To determine the feature set, the greedy algorithm and backwards elimination methods are used to narrow the features to the most impactful. To determine the number of clusters, the Davies-Bouldin method and “Elbow” method are used to estimate the optimal value for k .

K-means clustering often clusters around the extremes, which can be useful in identifying outliers, but might not be useful at finding broader clustering trends. After a first pass through of the commuter rail data for this analysis, the k-means algorithm was clustering around single-day and multi-day users. While this is a useful distinction, it required more clusters to further break down the clusters within each group. Thus, single-day riders were separated from multi-day riders and the clustering process was applied to both.

A.2 Feature Set Selection Process

Selecting a feature set to begin with depends on the data that is available and the goals of the analysis. The goal of this analysis is to categorize commuter rail users by temporal travel behaviors. Other studies that have used k-means clustering on transit data included spatial data as well (Basu, 2018). However, there is minimal variability spatially on commuter rail, whereas the other studies used bus or subway data which has greater spatial variability. Therefore, only temporal travel behaviors are included in this analysis.

From the available data, six features are included in the analysis: percent peak, percent weekend, average weekly trips, active days, active weeks, and range. The “percent peak” feature is, as the name suggests, the percent of trips that a user takes during the AM or PM peak hours, defined as trips before 9:00 AM and between 3:30 PM and 7:00 PM on weekdays. Because commuter rail trips begin around 5:00 AM at the earliest from the terminal stations and the travel time to North or South Station is around one to one-and-a-half hours, those trips are considered part of the AM peak by the MBTA. The “percent weekend” feature is the percent of trips taken on the weekend. “Average weekly trips” are the average number of trips taken per week that the user traveled over the study period. “Active days” indicates the number of unique days a user took commuter rail in the study period. “Active weeks” is the number of unique weeks the passenger took a trip on commuter rail. Each week is defined as starting on Monday and ending on Sunday. Finally, the “range” feature is the number of days between the first and last trip taken over the study period.

Clustering on the features would skew the results as the values are not comparable. For example, the “percent peak” feature is a value between 0 and 1, where 0 represents zero percent of trips were taken during the peak hour and 1 indicates 100% of trips taken on the peak hour. Conversely, the “range” feature has values between 0 and 31, representing the number of days between the first and last day traveled (it maxes out at the number of days in the month). Applying the clustering algorithm on these two features would overemphasize the “range” feature and undervalue the “percent peak” feature. To correct for this, a standardization process is used to make the features comparable to one another. The standardization puts each feature within the bounds of 0 to 1. The equation below shows the standardizing technique equation, where z_n is the standardized value, x_n is the original value, and $\min(x)$ and $\max(x)$ are the minimum and maximum values of the feature, respectively.

$$z_n = \frac{x_n - \min(x)}{\max(x) - \min(x)}$$

Figure A-1 shows the distribution of each feature standardized from zero to one for all mTicket users. The distributions of the features vary with a few having a skew towards one end. For example, the “percent weekend” has a significant skew towards 0%, which is expected as 95% of commuter rail trips occur on weekdays. “Percent peak” and “active days” have skews on the extremes as well, as many people ride infrequently (“active days,” “range,” and “average weekly trips” with right

skews) and during the peak hour (“percent peak” with many users at either extreme). Note that many of these skews towards the extremes are from single-day users. By definition, the single-day users traveled once, so the “active days” and “range” features show the single-day users around zero percent.

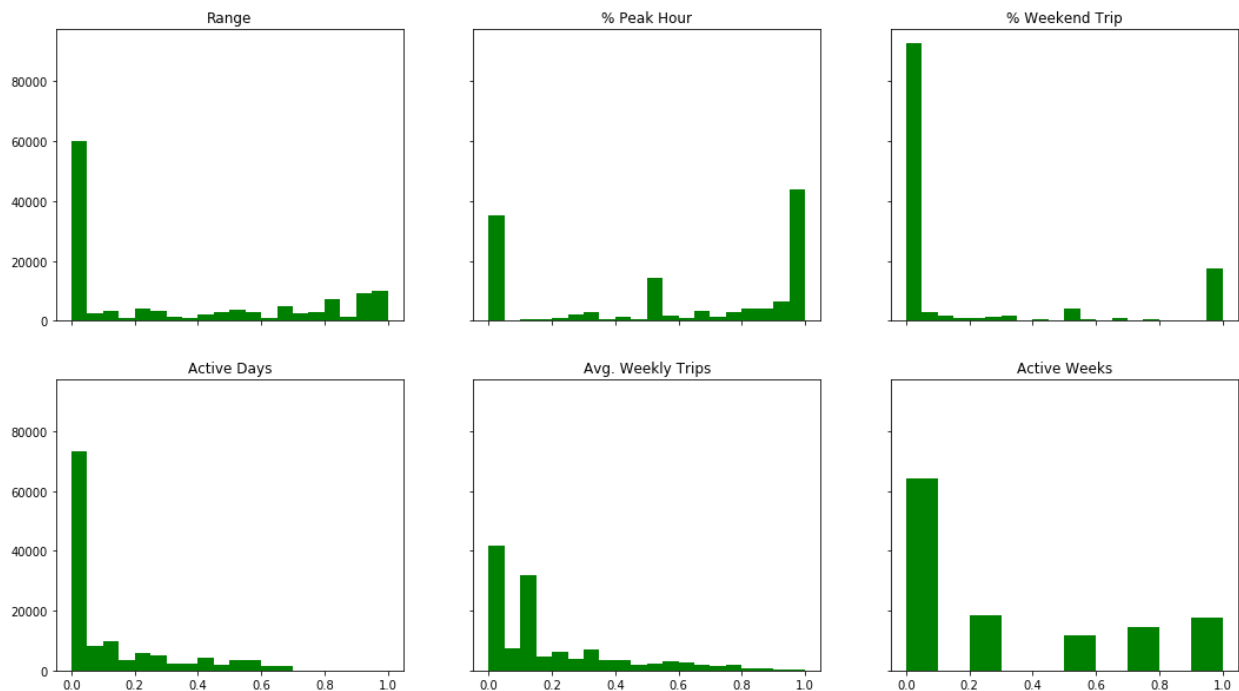


Figure A-1: Distribution of standardized features for multi-day users

While all the features could be used in the analysis, some of the features might be redundant or provide minimal additional information. To account for this and reduce redundancy, the greedy algorithm and backwards elimination methods are applied to the feature list. The greedy algorithm starts with one feature and applies k-means clustering to that lone feature. While it is possible that the number of clusters can affect the results of the greedy algorithm, there did not appear to be any significant changes to the data using between 5 and 10 clusters (6 clusters were chosen for this analysis). Once all of the data points are assigned a cluster, the cluster labels are kept and a second feature is included. K-means is applied to the new feature list and new cluster labels are assigned. The proportion of data points that shifted to another cluster is calculated. If this proportion is greater than a selected threshold (in this case 10%), then the feature provides additional information and should be kept. However, if the shift in clusters is below the threshold then the feature does not offer additional information and can be removed. Additional features are included and checked against the threshold until all features have been included.

The greedy algorithm is simple but effective at minimizing redundancy in the feature list selected. However, it is biased towards the order in which features are added. To check against this bias, the backwards elimination method is also applied. The backwards elimination method is similar to the greedy algorithm, except it begins with all features and removes them one at a time using the same threshold. This method is also prone to order bias but applies the feature selection in the reverse order compared to the greedy algorithm. Together, the greedy algorithm and backwards elimination methods can be used to remove redundant features and simplify the feature set. *Table A-1* shows the percent of multi-day users (data points) that did not change cluster for the greedy algorithm and

backwards elimination. Features that had more than 90% remain the same were eliminated from the feature set. The greedy algorithm began with the “range” feature and added features down the list. Backwards elimination starts with all of the features and removes them in reverse order of the greedy algorithm, starting with “active weeks” and ending with the “range.” From these methods, the “average weekly trips” and “active weeks” features did not provide enough additional information and were removed.

Table A-1: Greedy algorithm and backwards elimination for multi-day users showing the percent that did not change clusters. Eliminated features are in red.

Feature	Greedy Algorithm	Backwards Elimination
Range	-	51.4%
% Peak	49.6%	65.4%
% Weekend	77.4%	81.1%
Active Days	87.6%	72.6%
Avg Weekly Trips	87.8%	91.6%
Active Weeks	93.1%	-

For the single-day users, only the “percent peak,” “percent weekend,” and “average weekly trips” were used since, by definition, the “range,” “active days,” and “active weeks” features are homogenous for single-day users. Of the three remaining features, “percent peak” and “percent weekend” captured almost all of the variability among single-day users and were used in the analysis. Had the single-day users been included in the clustering process with multi-day users, the k-means clustering algorithm would have captured the zeros from single-day users in the “range,” “active days,” and “active weeks” features. Separating them out provides more granularity for multi-day users while still incorporating single-day variation.

A.3 Calculating k clusters

The hyperparameter for k-means clustering is the number of clusters, k . While selected k can be somewhat arbitrary, there are two methods that help suggest optimal values for k . The first is the Davies-Bouldin (DB) Index, which compares the within-cluster and between-cluster centroid distances. This method was created by David L. Davies and Donald W. Bouldin in 1979 as a way to evaluate the number of clusters selected (Davies & Bouldin, 1979). The closer the data is within a cluster and the farther apart the centroids are, the lower the DB score. A lower DB score is preferred as it means the data within a cluster is similar and the clusters are distinct from each other. However, as the number of clusters increases the DB score will naturally decrease. Thus, the lowest DB score might not always be the best as it might be too specific and uninterpretable. The better DB score would be where the value begins to plateau, as the increased number of clusters provide diminishing returns of benefit. Figure A-2 shows the results of the Davies-Bouldin method for multi-day users between two and fifteen clusters. Note that the score is lower at certain points (three, nine, and thirteen clusters) but fluctuates based on the number of clusters. This is because some clusters might line up better with the data clusters and adding an additional cluster might shorten the inter-cluster distance, causing the DB score to increase.

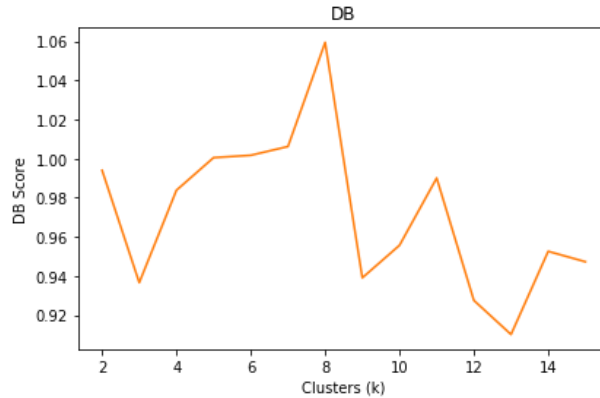


Figure A-2: Davies-Bouldin score by number of clusters from 2 to 15

The other method to determining the number of clusters is through the “elbow” method. This method uses the sum of squared differences (SSD) between clusters. The SSD will naturally decrease with an increase in the number of clusters, just as it does with the DB Index. However, when plotting the SSD by the number of clusters, there is a “kink” in the plot where the SSD begins to plateau, forming an “elbow” shape. Thus, the point of the elbow is where the ideal number of clusters would be. Any increase in the number of clusters would provide marginal gains. Figure A-3 shows the results of the “elbow” method for multi-day users. As can be seen from the graph, the “elbow” occurs around six clusters. After that, the benefits in SSD diminish with each additional cluster added.

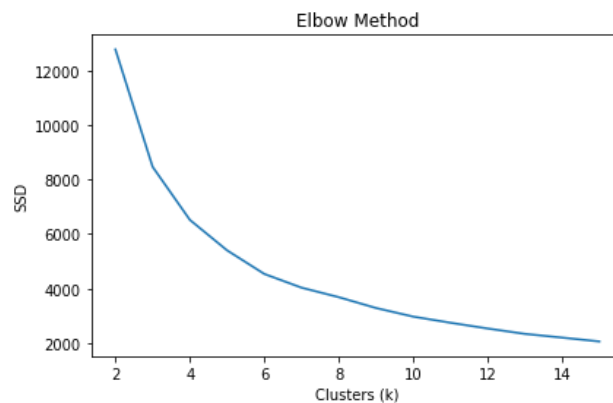


Figure A-3: "Elbow" method for 2 to 15 clusters

After reviewing the DB Index and “Elbow” method, as well as examining the clusters visually, this analysis will use six clusters for multi-day users. While using nine clusters would yield a better DB score, the interpretation was harder to parse with the increased number of clusters. Instead, six clusters provides better interpretation and relatively clear clusters. It is also the “elbow” point in Figure A-3, meaning more clusters would only provide slightly better cluster definitions. This section did not mention single-day riders. That is because the process of selecting features and clusters was simpler. There were only three potential features to select from, of which only two proved relevant (“percent peak” and “percent weekend”). For determining the clusters, the “elbow” method and DB score both indicated four clusters as optimal. This is evident from Figure A-4 which shows four nearly homogenous clusters for single-day users.

A.4 Clustering Results

The data was split into two groups, single-day and multi-day riders, of which there are four clusters from the single-day riders and six clusters from the multi-day riders. Single-day riders constituted 43.4% of mTicket users in January 2020 but only 8.3% of all trips taken. Since these riders were only on the system one day, their clustering behavior was clear-cut. The only two features that distinguished these users was percent of their trips taken during the peak (*peak_n*) and percent of their trips taken on the weekend (*weekend_n*). Figure A-4 is a heatmap of each single-day mTicket user's behavior in January 2020. Each horizontal line on the figure represents one single-day user, with the percent peak and percent weekend trips shaded by the ridership behavior. For example, the cluster on the top has all users with 0% of their trips during the peak and 100% of their trips taken on the weekend. The size of the *cluster_label* column represents the number of users that are categorized in that cluster within the single-day cluster. Note that the size of the clusters depicted is not scaled, but the percent on the label is scaled using the methods described in Section 3.3. From this heatmap, there are four clear clusters that are formed: Weekend, Peak, Off-Peak, and Half-Peak. These cluster labels describe the type of behavior experienced by each user.

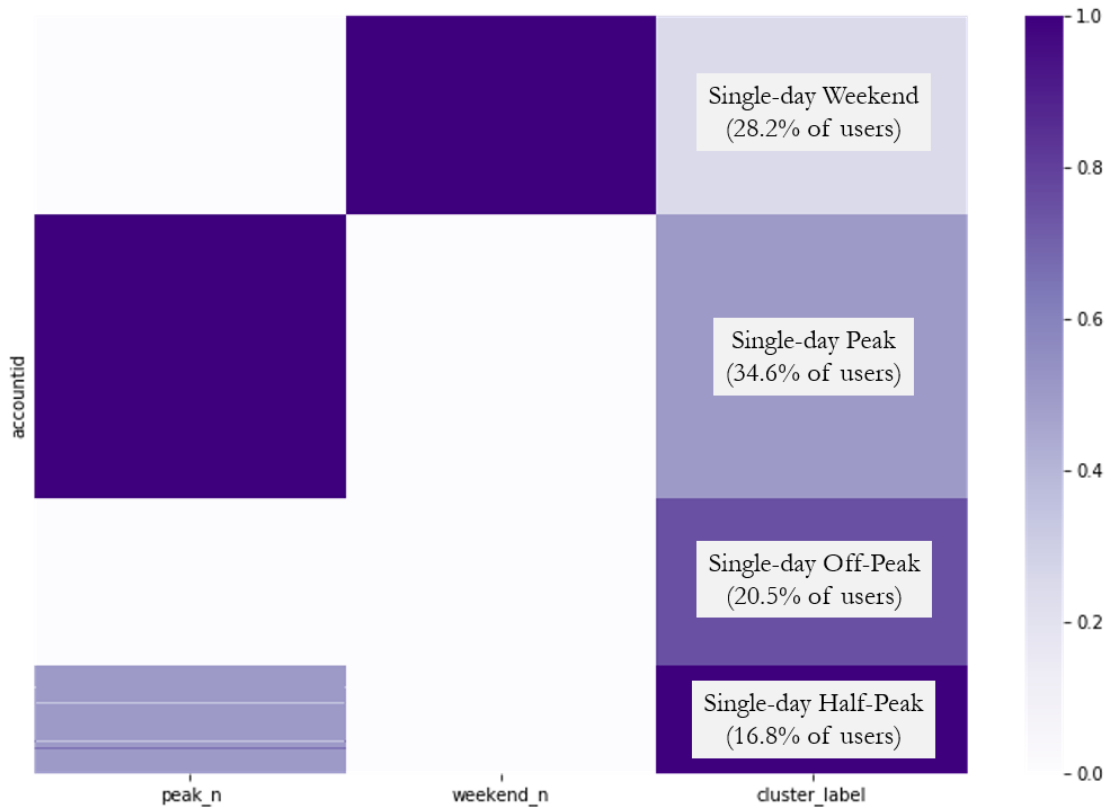


Figure A-4: Heatmap of mTicket single-day users' travel behavior in January 2020

Multi-day riders are defined by the number of unique days they traveled normalized to all possible days traveled (*active_days_n*), percent of their trips taken during a peak hour (*peak_n*), percent of their trips taken on the weekend (*weekend_n*), and the range of their days traveled normalized by the longest possible range (last day - first day, *range_n*). Figure A-5 shows a heatmap of multi-day riders for each feature (active days, peak, weekend, and range). As with the single-day users, each horizontal line (more distinguishable on this graph) is one mTicket account ID, shaded by their

travel behavior for each feature. The Occasional Peak cluster has a moderate number of active days traveled, a high percent of their trips during the peak, low percent during the weekend, and a fairly high range of travel. These users have an occasional ridership (based on the moderate number of active days traveled) and almost always ride during the peak hour, thus defining its label. The cluster labels for these riders are shown in the *cluster_label* column. Note that the heatmap is not scaled to overall commuter rail ridership, but the percent of users indicated on the cluster label is scaled.

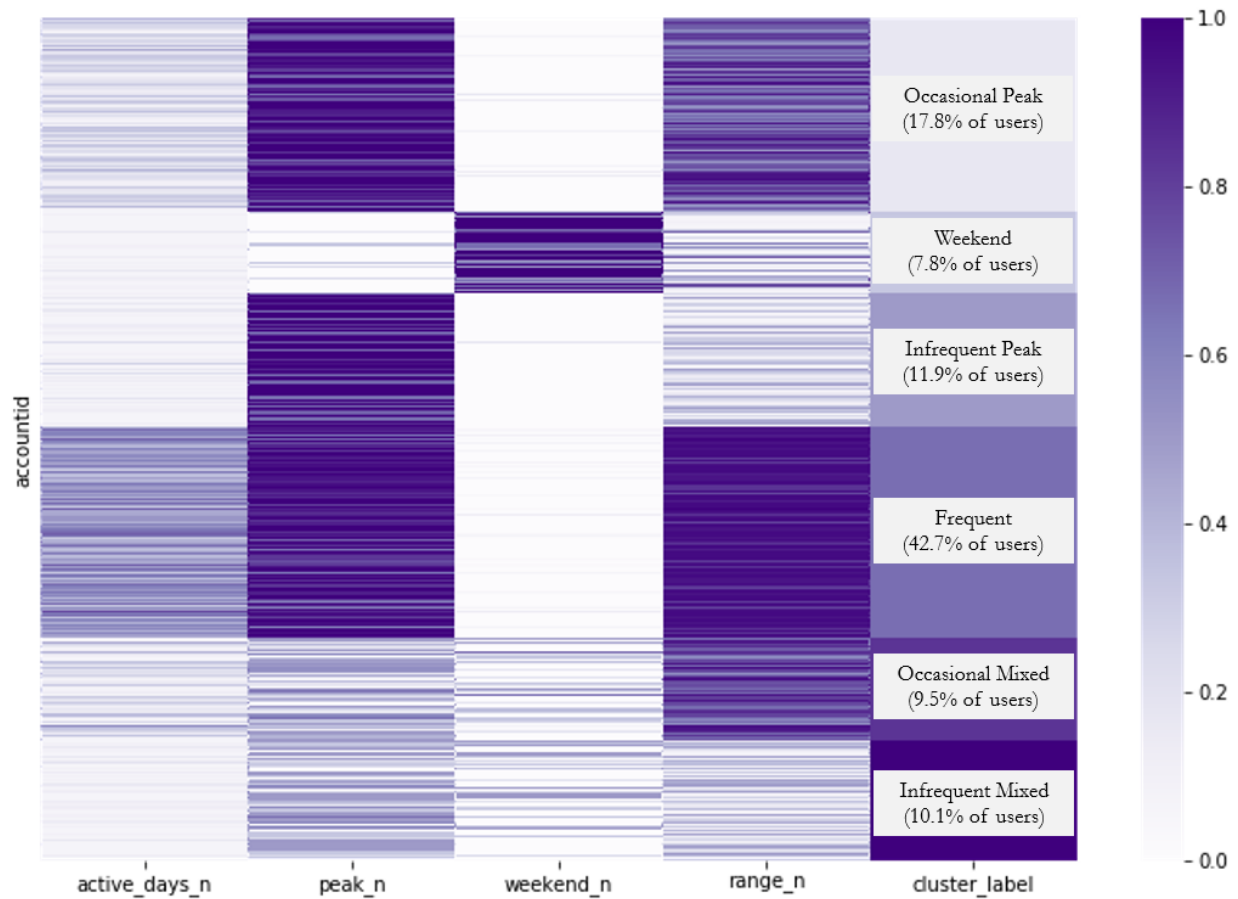


Figure A-5: Heatmap of mTicket Multi-day users' travel behavior in January 2020

Taken together, there are ten clusters in the analysis. Figure A-6 shows the distributions of the four features within each cluster. Note that none of the single-day clusters used the *active_days_n* or *range_n* features, since, by definition, they all rode one day with a range of zero. The clusters are separated by frequency of travel and time of usage. Figure A-6 *Figure 3-9* shows how the Frequent cluster has the highest active days and range compared to the other clusters. They also happen to mostly travel during the peak, which suggests they are traditional commuters who travel during the morning and evening peak hours. The two “occasional” clusters have similar active days and range distributions but differ on what how much they ride during the peak hours. The “infrequent” and “weekend” clusters have the lowest active days and range of the multi-day clusters but differ depending on if they travel during the peak hours or weekend.

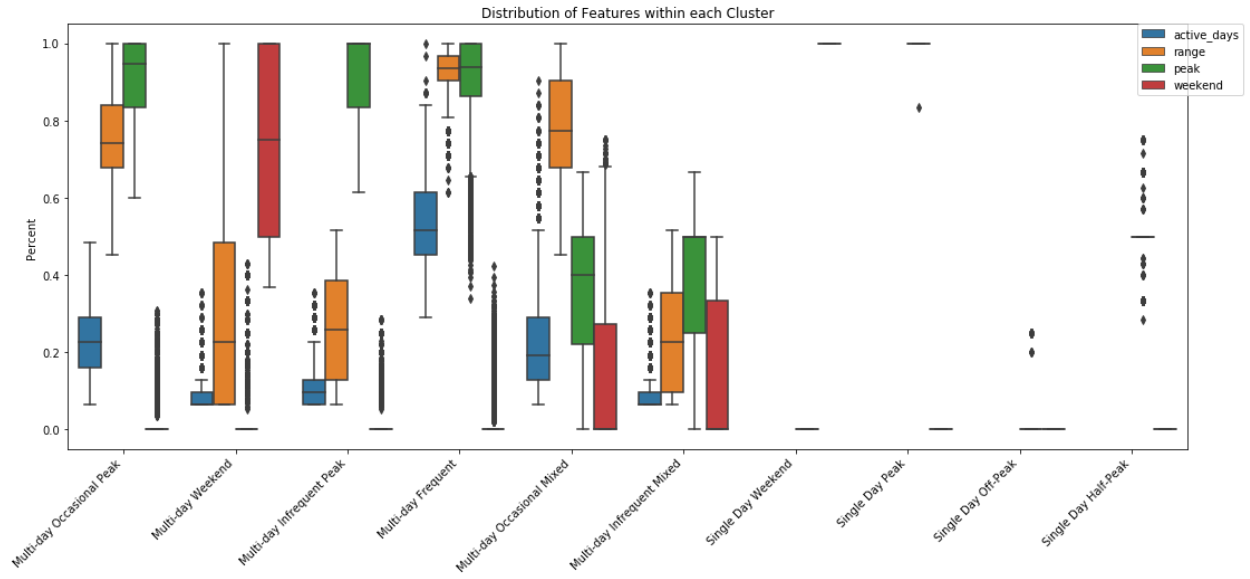


Figure A-6: Distribution of users in each cluster by feature. Single-day features often appear as a flat line, indicating no variability in the feature.

Appendix B: 2-Proportions Test

In the 2-Proportions Test, the success of one method is compared to another. The Null Hypothesis assumes that the treatment (p_2) acceptance rate (percent of monthly passes purchased compared to the control) is no different than the acceptance rate for the control (p_1). The Alternative Hypothesis is that the treatment increased the acceptance rate of monthly passes compared to the control. For statistical significance, a significance level of $\alpha = 0.05$ is considered. The Monthly Pass Campaign experiment uses the one-tailed test, since the goal was to increase monthly pass purchases with the treatment applied. The critical value we are comparing is $z_c = -1.64$.

$$H_0: p_1 = p_2$$

$$H_1: p_1 < p_2$$

The z-statistic is computed using the below equation. \hat{p}_1 is the proportion of acceptances for the control while \hat{p}_2 is the proportion of acceptances for the treatment. For example, $\hat{p}_2 = \frac{59}{341} = 0.173$ for the Above Recent group. \bar{p} is the combined proportion from the control and treatment. For example, $\bar{p} = \frac{59+75}{341+477} = 0.1638$ for the Above Recent group. n_1 and n_2 are the sample sizes for the control and treatment groups. If the resulting z-score is greater or equal to z_c , which is -1.65, then we can reject the null hypothesis. If the resulting z-score is less than z_c , then we cannot reject the null hypothesis and will not have enough evidence to believe that the treatment increased monthly pass purchases in the sample.

$$z = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\bar{p}(1 - \bar{p}) \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}}$$

Table B-1 shows the results from the pilot experiment for October monthly pass candidates. From a quick glance, it appears that the treatment group (the one that received the email notification) had a slight increase in pass purchases compared with the control group. However, the difference is small and a statistical test is necessary to see whether the email notification treatment really did increase pass purchases or if there is inconclusive evidence to support that claim. Table B-2 shows the p-values for each group using the 2-Proportions Test. A p-value below 0.05 means the null hypothesis can be rejected at the 95th percentile. Based on the 2-Proportions Test, no group had a p-value below the 0.05 threshold and therefore the null hypothesis cannot be rejected for any of the groups.

Table B-1: Number of October monthly passes purchased in treatment and control groups

Updated Email Groups	Sample			Control		
	# Passes	Total	Percent	# Passes	Total	Percent
Above Recent	59	341	17.3%	75	477	15.7%
Near Recent	39	348	11.2%	45	486	9.3%
Consistent Recent	19	584	3.3%	11	512	2.1%
Consistent Non-recent	25	406	6.2%	24	497	4.8%

Table B-2: P-value from 2-Proportions Test

Group	Treatment %	Control %	p-value
Above Recent	17.3%	15.7%	0.274
Near Recent	11.2%	9.3%	0.178
Consistent Recent	3.3%	2.1%	0.132
Consistent Non-Recent	6.2%	4.8%	0.190

Appendix C: MIT Mobility Pass

In 2016, MIT and the MBTA conducted a pilot of the Mobility Pass, where MIT offered universal, fully subsidized transit to its employees and was charged by the MBTA on a per-use basis for all bus and subway trips taken by its employees. In addition to the Mobility Pass, MIT restructured their transportation benefits for all employees in what they labeled “AccessMIT.” Other changes to the transportation benefits included a shift from annual parking passes to a daily parking charge¹⁰, an increase in the commuter rail pass subsidy, a new subsidy for transit station parking, and the addition of an online commuter dashboard. AccessMIT served multiple goals for MIT, from reducing carbon emissions, to improving transportation benefits, to (what might be the most important factor) reducing parking demand on campus in order to demolish deteriorating parking garages and smaller surface lots in order to construct new campus buildings.

C.1 AccessMIT Transportation Benefits

Prior to AccessMIT, employees were offered a 50% subsidy on all transit passes and parking passes were annual. AccessMIT provides fully subsidized bus and subway trips (through the Mobility Pass), an increase to a 60% subsidy on commuter rail passes, and a switch from annual to daily parking. The switch from annual to daily parking reflects the interest in providing flexibility for MIT employees. Annual passes are sunk costs that employees would have to make at the beginning of each year. After purchasing an annual parking pass, an employee is more likely to drive to work given they have already paid for full year of parking. A daily parking charge allows employees to drive some days and take transit other days. This increases modal flexibility for employees, especially when paired with fully subsidized bus and subway trips.

C.2 MIT Data Sources

The MIT pilot provided a rich dataset to analyze the effects of the Mobility Pass. Each MIT ID is embedded with an MBTA CharlieCard microchip that is used to charge each transit trip that was taken and the mode by which it was taken (bus or subway). Additionally, the MIT ID is used to access most parking facilities on campus¹¹ and each daily parking usage is recorded. This creates a disaggregate dataset of employee parking and transit behavior. However, prior to the Mobility Pass, MIT employees purchased either passes through the Corporate Program (now Perq) or pay-as-you-go tickets separately. These passes were unable to be traced back directly to individual MIT employees. In addition, MIT conducts a biennial commuter survey that asks employees and students how they commute to campus using a weekly trip diary format. These surveys could be linked to MIT IDs and can be used to estimate detailed travel behaviors by employees.

C.3 Institute-wide Transportation Shifts

MIT employs over 10,000 employees, roughly 90% of which are benefits-eligible for the transportation benefits. All benefits-eligible employees were offered the AccessMIT transportation benefits options. Additionally, MIT has increased its number of employees by roughly 2% each year. The analysis of the MIT Mobility Pass has been performed for the period from the 2014-15

¹⁰ The daily parking charge was set at \$10 but total annual parking charges were capped at the price of the previous year’s annual parking pass.

¹¹ There are a few parking lots that do not have gated entry and are spot-checked for compliance. Those lots are not equipped for daily parking charges and require monthly parking passes.

Academic Year to the 2018-19 Academic Year. The COVID-19 pandemic caused most of MIT to go remote immediately following the first stay-at-home orders, with limited campus accessibility throughout the 2020-21 Academic Year. During the COVID-19 pandemic, MIT removed all parking fees for all students, faculty, and staff to reduce cost burdens on the few staff who needed to work on campus. For that reason, the analysis focuses on the first three academic years following the implementation of the Mobility Pass.

Following AccessMIT, the number of parking permits has seen a decrease from 2015 to 2019 while the number of active transit passes has steadily increased each year (see Table C-1). Annual parking permits were limited to non-gated lots and leased off-campus lots starting in 2016, shifting many of the annual permitholders to daily parking permits. Even still, there was a reduction in parking permits in the 2016-17 academic year, a trend which continued to 2018-19. The 2017-18 year only goes until April 2018 (based on data from (Rosenfield, 2018)). LinkPasses accounted for 3,658 passes in the 2015-16 school year, while active Mobility Passes averaged roughly 6,000 in the first academic year, increasing to 6,400 by 2018-19. Note that LinkPasses were subsidized by 50% before AccessMIT and only offered to employees who requested them. With the Mobility Pass (after 2016), any employee who used transit at least once each month is considered an “active” Mobility Pass account.

Table C-1: Parking permits and transit passes per academic year

	2015-16	2016-17	2017-18	2018-19
Daily Parking Permit	2248	3793	3458	3617
Annual Parking Permit	2618	829	744	789
Carpool Parking Permit	304	273	283	340
All Parking Permits	5170	4895	4485	4746
Local Transit Pass	3658	5977	6201	6463

Daily parking (calculated as the number of employee-days parked) at MIT decreased from 493,000 to 475,300 in the first year of AccessMIT and saw similar numbers in the 2018-19 academic year, despite an employee growth rate of roughly 2% per year (see Table C-2). The 2017-18 academic year is based on an estimate from September to the end of April, scaled up to account for the rest of the year. Comparing data from September to March (not including March), the 2019-20 academic year saw an increase in daily parking from 218,500 to 228,800. Linked trips on the Mobility Pass have increased from 1.66 Million to 1.72 Million from 2016 to 2019. Comparing data from September to March again, the increasing use of transit continued in the first half of the 2019-20 academic year (before the pandemic).

Table C-2: Daily parking and linked trips by employees per academic year

Parking	AY2015-16	AY2016-17	AY2017-18	AY2018-19	AY2019-20
Sept. - Mar.	233,176	219,682	203,886	218,482	228,829
Sept. - Apr.	313,694	299,852	277,345	299,156	-
Full Year	493,247	475,293	437,848	476,868	-
Transit					
Sept. - Mar.	-	796,148	816,113	841,322	857,463
Full Year	-	1,659,665	1,654,005	1,720,151	-

Another dataset is the MIT biennial commuter survey. This survey is conducted in the Fall semester on even years, with the most recent one being conducted in 2018 (a survey was skipped in 2020 due to the pandemic). While the survey is optional, it is distributed to all faculty, staff, and students and always generates a response rate above 50%. Based on this survey, employees increased their public transit usage and decreased their drive alone rates. There are two metrics used to estimate the mode of choice by MIT employees: a primary and secondary mode question and a trip diary of the previous week. The primary mode shows a decrease in drive alone rates by MIT staff from 29% to 24.8% and a simultaneous increase in public transportation rates from 44.2% to 49.6% between 2014 and 2018 (see Figure C-1). The drive alone rate remained the same in 2016 and 2018 but the public transportation rate increased by 1.9 percentage points. The 2018 survey saw a decrease in walking, cycling, and carpooling compared to 2016 and a slight increase in work from home and transportation network company (TNC) or taxi use.

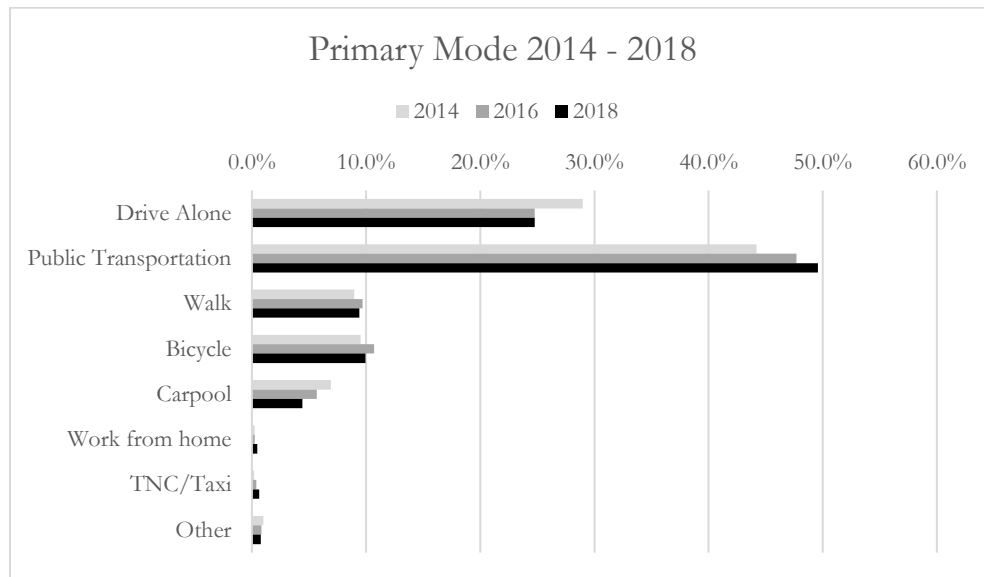


Figure C-1: Primary mode responses from 2014 to 2018

The survey also asked respondents to indicate a secondary mode, if they had one. There were only 38% of employees who did not indicate a secondary mode choice, illustrating the multi-modal preferences of employees. From Figure C-2, public transportation was the most common secondary mode listed among those who indicated a secondary mode choice, with “other” and drive alone as the next highest. The “other” category includes working from home, taking a TNC or taxi, vanpool, and other modes that do not fit any category. The secondary mode question was first added in the 2016 survey.

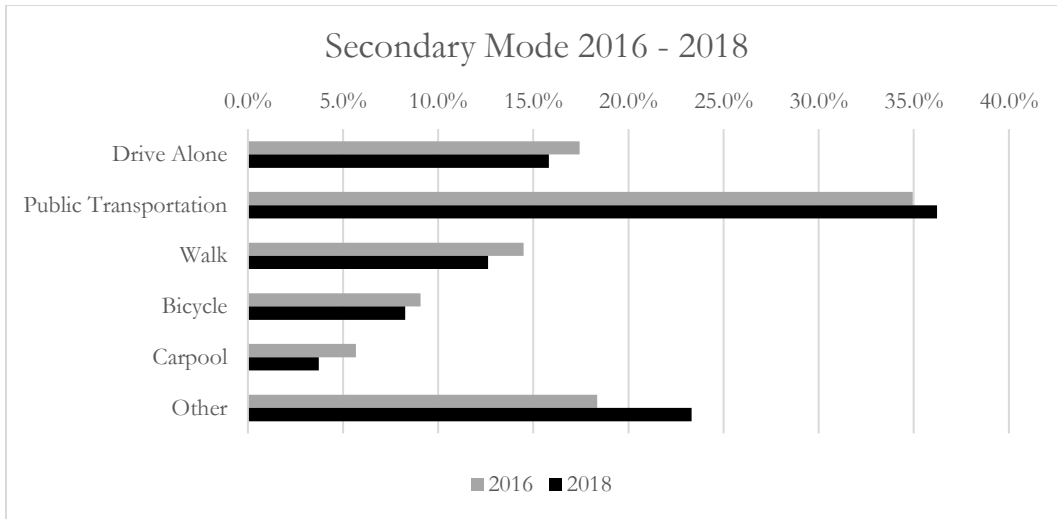


Figure C-2: Secondary mode responses, if they had one, from 2014 to 2018

The commuter survey includes a series of questions (in the form of a trip diary) asking respondents how they commuted to MIT the previous week in the mornings. The trip diary is helpful in understanding frequency of commuting trips and multi-modal tendencies. For example, if someone drives to work on Monday and Tuesday, rides their bike on Wednesday, and takes the T on Thursday and Friday, they might indicate that they primarily take transit or drive, with the other being their secondary. But that wouldn't capture their bicycle trip or the frequency of driving compared to taking public transit. While the trip diary only offers a glimpse of respondents' commuter patterns (only captures one week), it provides greater detail on the user behavior than the primary and secondary mode questions.

Figure C-3 shows the percent of commute-days for each mode based on the trip diary. The trip diary covers a full week (Monday to Sunday) and allows respondents to input days they did not work. The percent for each mode was calculated by summing the days a mode was taken to work and divide it by the total number of days a person worked at MIT. The trip diary shows a similar rate for drive alone but a lower rate for public transportation than the primary mode question. While the primary mode question showed almost 50% of employees using public transportation to commute to MIT, the trip diary indicates that on 44.2% of work days a commute trip was made by public transportation. The work-from-home rate is also significantly greater in the trip diary than it is in the primary mode (6.7% in 2018 compared to 0.5% from the primary mode question). Note that this was taken before the global pandemic, when work-from-home was much less common. The difference between the trip diary and primary mode is important to note, as many employees (before COVID-19) would take a day or two to work-from-home each week. It is likely that this flexibility will increase when MIT fully opens its campus up again.

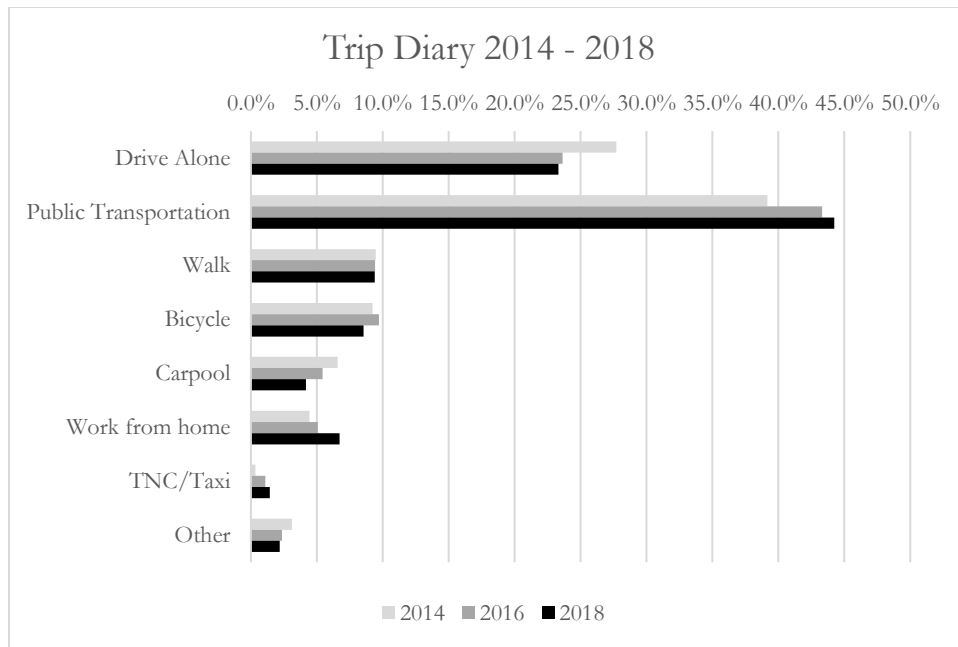


Figure C-3: Trip diary responses from 2014 to 2018

While the overall parking and transit trends show an increase in transit and a decrease in drive alone rates, it is unclear if the driver alone mode is shifting to transit or if user of other modes (such as carpool, walking, or cycling) are shifting to transit. One way of finding out how people have shifted their behavior is by asking them if they switched and, if so, what they were using before. The commuting survey included a question asking users if they changed their primary or secondary mode in the previous year. This is a helpful question to find out if the new AccessMIT benefits persuaded people to switch modes, and what modes the respondents previously used.

Figure C-4 (from (Rosenfield, 2018)) shows a Sankey diagram of the primary or secondary mode shift for the 2016 commuter survey. There were 15% of employees in 2016 who indicated changing modes within the prior year (2015). Of these, there was a larger portion of drive alone commuters switching to transit (17%) than vice-versa (8%). In the 2018 commuter survey (Sankey diagram on Figure C-5), 13.8% of employees (who were working at MIT in the prior year) indicated a mode change from 2017 to 2018. In those years, there was a slightly greater shift from drive alone to public transportation (5.9%) than vice-versa (4.9%) but still much less of a shift than as a result of the debut of AccessMIT. Roughly a quarter (25.3%) did not change their primary mode choice, implying they changed their secondary mode choice.

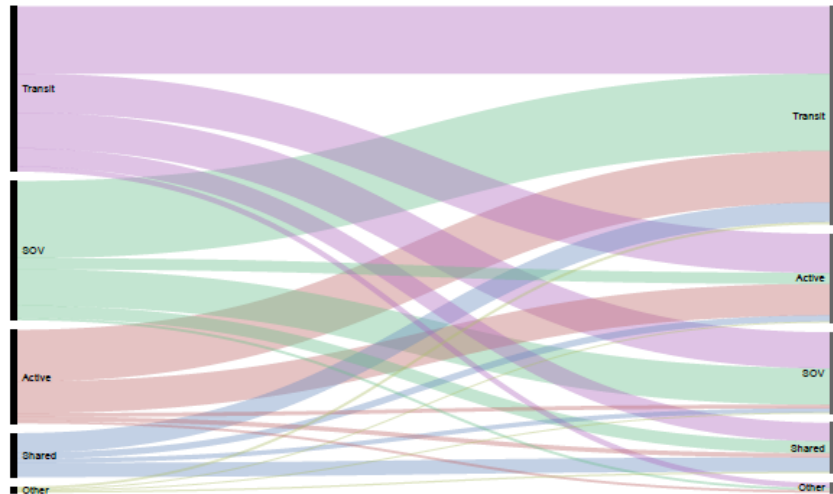


Figure C-4: Mode shift from 2015 (left) to 2016 (right) among survey respondents who reported changing their commute mode. Those shifting to the same mode imply a change in secondary modes. Taken from Rosenfield, 2018.

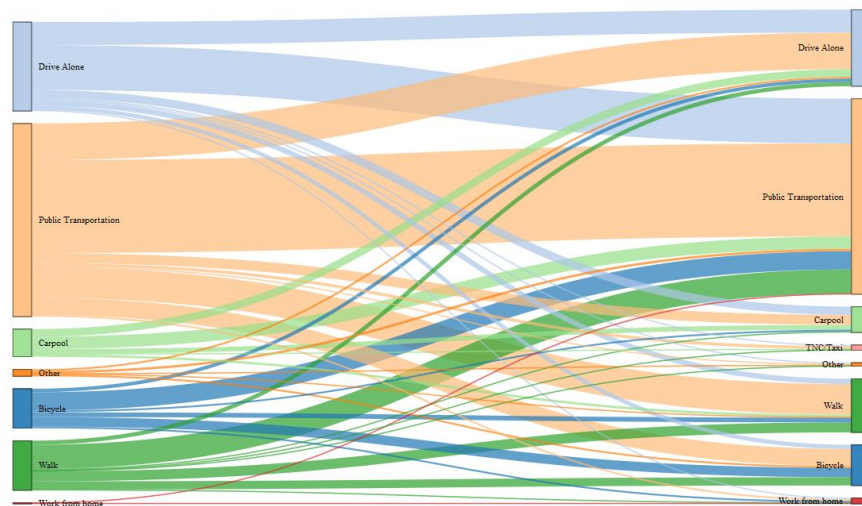


Figure C-5: Mode shift from 2017 (left) to 2018 (right) among survey respondents who reported changing their commuting mode. Those shifting to the same mode imply a change in secondary modes.

Another component of AccessMIT was to create competitive transportation benefits for employees to draw and retain top talent. The biennial commuter survey asks respondents how satisfied they are with the transportation benefits offered to them. Figure C-6 shows the employee satisfaction with the transportation benefits offered at MIT between 2014 and 2018 and Figure C-7 shows the employee satisfaction with the transportation benefits broken down by their primary mode in 2018. Employees have been pleased with AccessMIT with over 85% of employees either somewhat satisfied or very satisfied with the transportation benefits in 2018. Employee satisfaction increased from 75.9% to 84.6% in the first year of AccessMIT. That increased to 85.6% in 2018. Employees appear to appreciate the flexible benefits offered through AccessMIT, which was a goal for MIT.

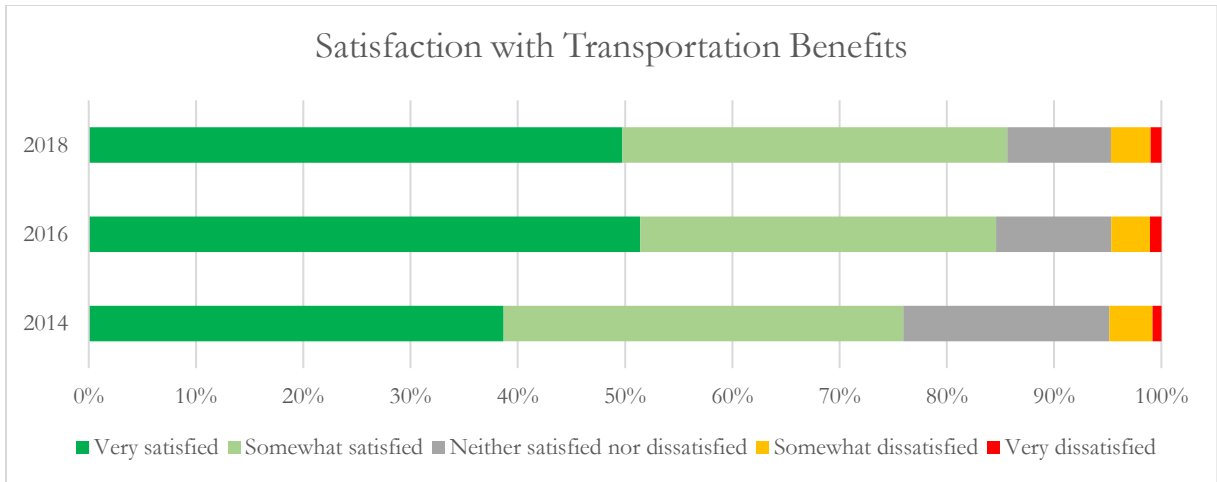


Figure C-6: Employee satisfaction with the transportation benefits offered at MIT from 2014 to 2018.

Satisfaction with the transportation benefits is highest with employees who indicate public transportation as their primary mode of commuting. Walking and cycling have the next highest satisfaction levels with AccessMIT. This is interesting as there are no direct financial benefits to employees who walk to MIT. However, it is likely that many employees who walk to campus also take transit and would benefit from the fully subsidized Mobility Pass. It is likely that employees who walk to MIT would also live near transit stations and could benefit from taking transit outside of work. For cyclists, MIT offers a discounted BlueBikes (the local bike share system) membership as well as bike parking facilities around campus. Employees who primarily drive to work show the lowest satisfaction levels with the transportation benefits, although over 70% are still somewhat or very satisfied with the transportation benefits. While the annual pass was replaced with daily parking fees, these are capped at the annual rate to avoid unfairly charging employees who cannot access campus from alternative modes.

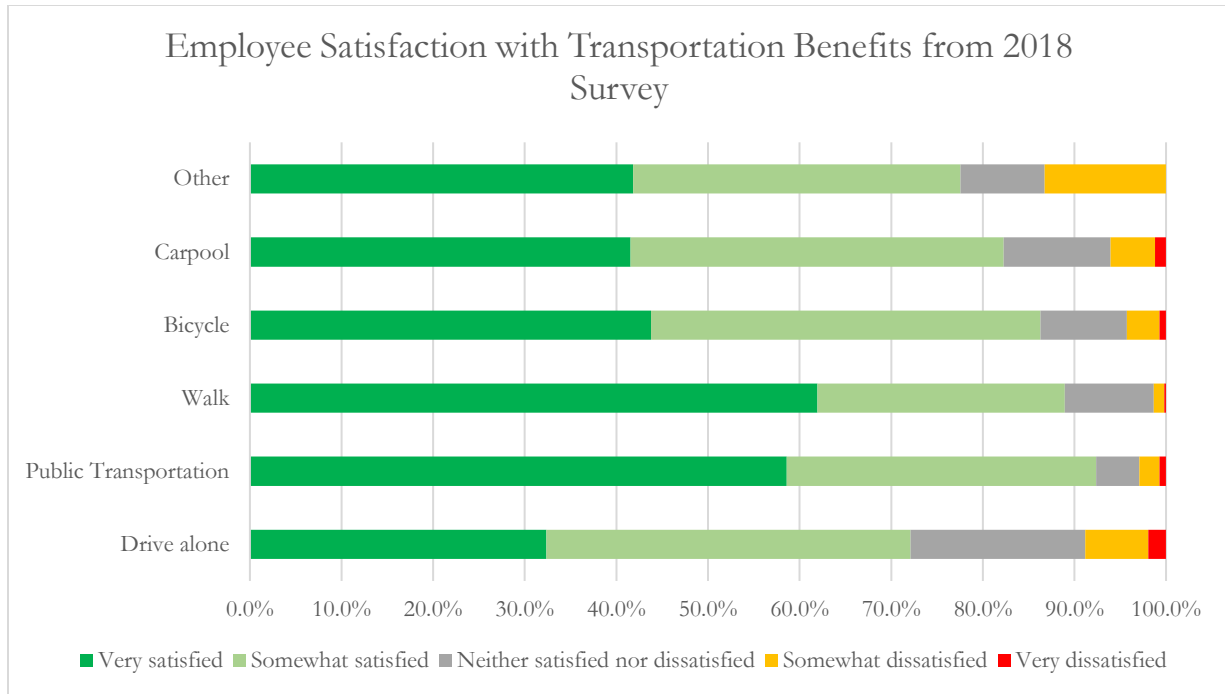


Figure C-7: Employee satisfaction with the transportation benefits offered at MIT in 2018 by primary mode response

C.4 Panel Data

At the institute-wide scale, it appears AccessMIT was able to moderately shift users away from driving and towards transit through daily parking and fully subsidized transit. However, who were the users who switched to transit? Who stopped driving? To try to answer these questions, this subsection follows employees who were employed at MIT between 2014 and 2019 and responded to the biennial commuter surveys between 2014 and 2018. This panel does not represent all employees as there is churn among employees, which is not captured, and the potential self-selection bias of employees who consistently respond to the panel. However, it is helpful in showing how commuting preferences change for individual users based on the transportation benefits that are offered.

This subsection aims to see how AccessMIT has affected the mode choices of the panel and to see how their mode choices shift over time. Based on the primary commute mode of choice, those employees in the panel group showed a slight increase in public transportation and a slight decrease in driving alone, especially between 2014 and 2016 (see Figure C-8). However, the trip diary tells a slightly different story. Figure C-9 shows how public transit usage decreased slightly, rather than increased, while driving alone decreased similar to the primary mode. In general, respondents are more likely to say they primarily take transit to MIT than shows in the trip diary. This is potentially due to the higher availability of alternatives for transit riders. Employees who walk and cycle to MIT on occasion might also take transit. They might say they primarily take transit to campus but switch between the T and walking or cycling.

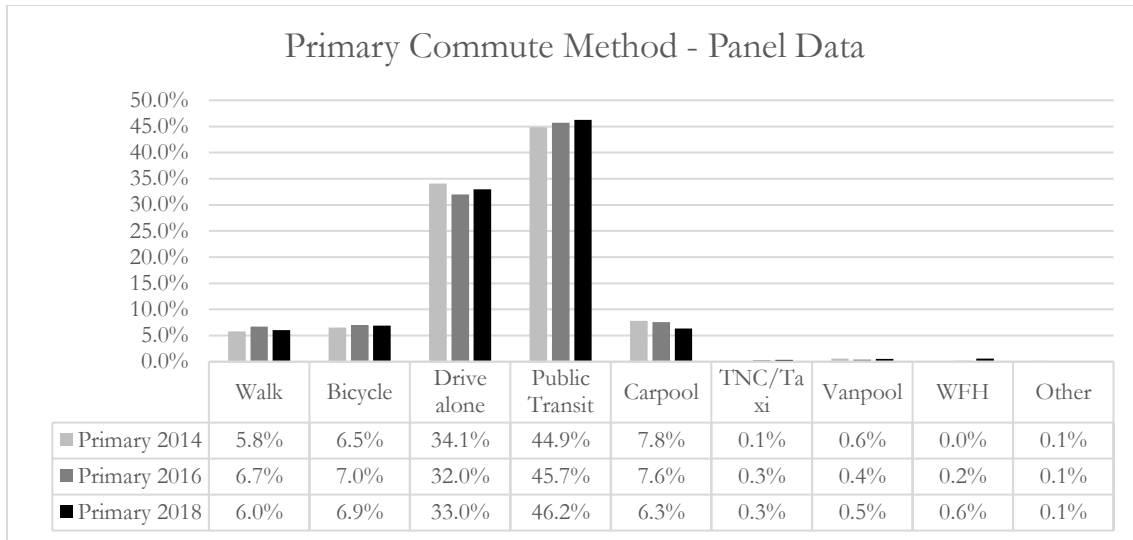


Figure C-8: Primary mode by employees who answered the commuter survey in each of the three biennial surveys between 2014 and 2018

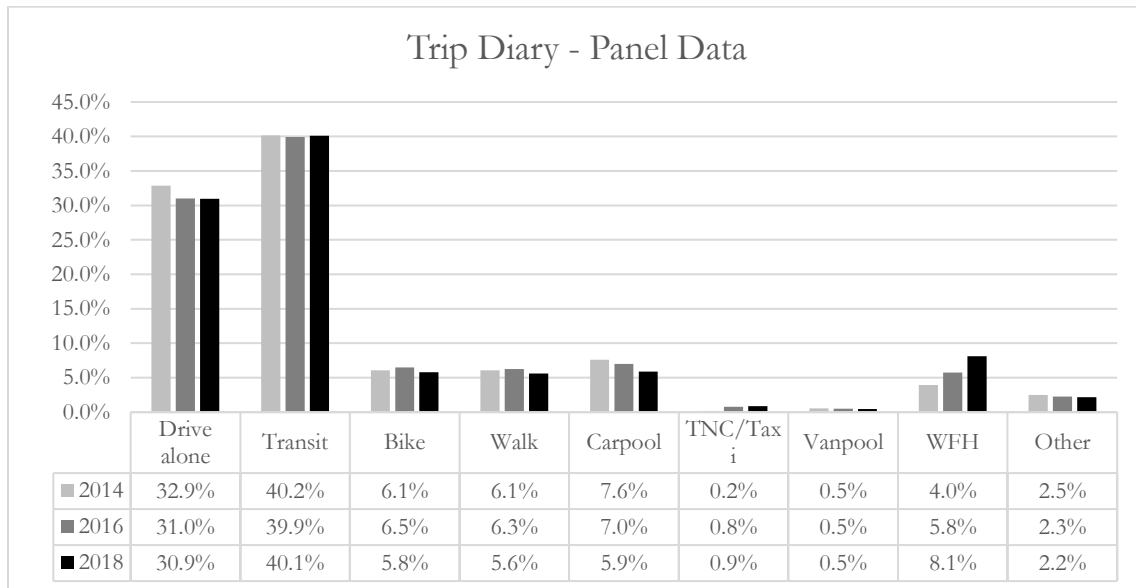


Figure C-9: Trip diary by employees who answered the commuter survey in each of the three biennial surveys between 2014 and 2018

For the same panel of employees, the parking data shows a decline in usage during the first year of AccessMIT. However, the parking data also shows an increase in average days parking on campus in the subsequent years after the launch of AccessMIT. Note that the data source used in 2018-19 for parking was different than the data used in the previous years. The MIT Parking and Transportation Department changed parking access vendors in the fall of 2018, potentially causing discrepancies in the data between the two years. Table C-3 compares the trip diary responses from the panel on the average number of days an employee drove alone to MIT with the average days a panel employee parked on campus (using the parking data from their MIT ID). The trip diary shows a decrease in average days driving alone to campus from 1.61 to 1.52 days per week while the parking data shows a lower number although with still a decline from 1.11 to 1.06 days parked per week. The increase in days parked per week in 2017-18 could potential reflect the shift in employee preferences the longer they work at MIT and the higher their pay. Additionally, there was a \$100 fee for ordering a daily

parking permit in 2016-17 that was removed in 2017-18, reducing the barrier to access for a daily parking permit.

Table C-3: Average days parked per week based on parking data and the trip diary

PARKING	2014-15	2015-16	2016-17	2017-18	2018-19
Parking Data	-	1.11	1.06	1.10	1.27
Trip Diary	1.61	-	1.52	-	1.52

Table C-4 shows the average days taking transit based on MBTA transit taps (from the MIT ID) and the trip diary. Every two linked trips accounted for one day taking transit. Data on average trips taken before AccessMIT is not available given those employees did not have their transit passes on their MIT IDs. However, (Rosenfield, 2018) estimates that average daily transit ridership increased by 14% from 2015-16 to 2016-17. In addition, the average daily transit ridership increased from 0.95 to 1.07 days per week from 2016-17 to 2018-19, an increase of 13% over those two years.

Table C-4: Average days taking transit per week based on transit tap data and the trip diary

TRANSIT	2014-15	2015-16	2016-17	2017-18	2018-19
Transit Data	-	-	0.95	1.02	1.07
Trip Diary	1.75	-	1.86	-	1.83

C.5 New Employees

Turnover at MIT is roughly 30% every two years, so the impact from new employees is significant. There are two components to the new employee analysis. The first examines new employees every two years (i.e. did not work in 2014 but did in 2016) while the second looks at how new employees change their commuting behavior over time (i.e. the modal trends from those who began working just before 2016 looking at their 2018 data). This distinction is helpful as new employees tend to be younger and have lower paychecks. Both of those factors often result in increased transit usage and lower drive alone rates.

New employees are known for the 2016 and 2018 surveys. They are defined as employees who were not employed at MIT when the previous commuter survey was released, meaning they have worked at MIT for less than two years. Figure C-10 shows the primary mode share for new employees in 2016 and 2018. New employees are more likely to ride public transportation and less likely to drive compared to the overall employee average. In 2016, 47.7% of all MIT employees had their primary mode as public transit, whereas this number was 55.8% for new employees. A quarter of all employees indicated driving alone as their primary mode whereas only 12.2% of new employees indicated driving alone as their primary commute mode. Similarly to the primary mode, the trip diary shows a lower drive alone rate and higher transit rate than all employees in each given year (see Figure C-11 *Figure 5-11*) This matches the general understanding that new employees are likely to earn less and, therefore, less likely to own a vehicle and drive to work. Additionally, new employees are more likely to live closer to work (in the core areas of Cambridge and Boston) than their older, more experienced counterparts.

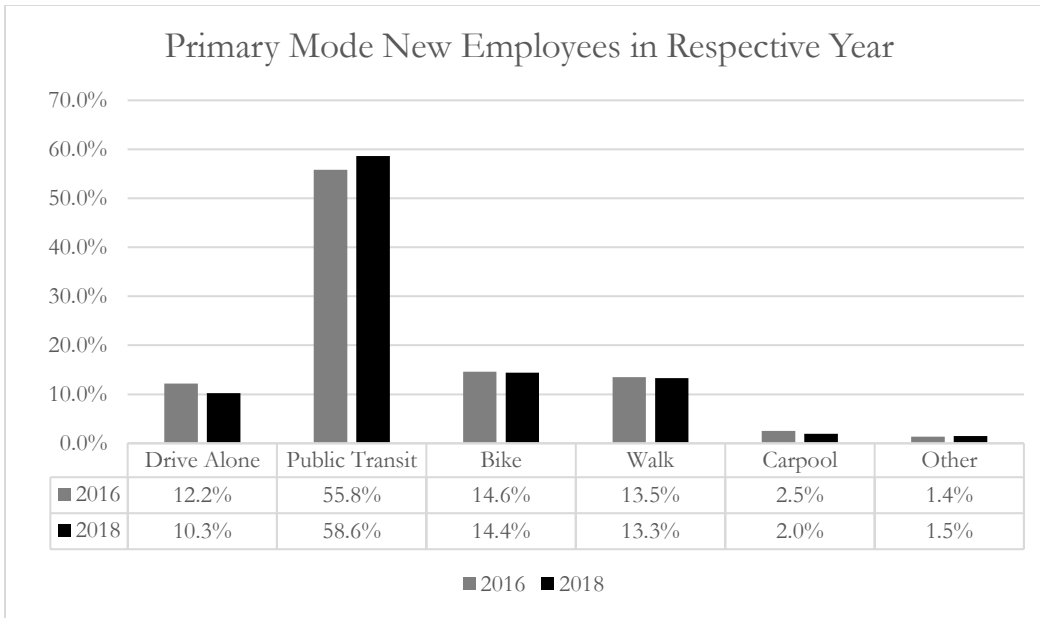


Figure C-10: Primary mode by new employees in each respective year

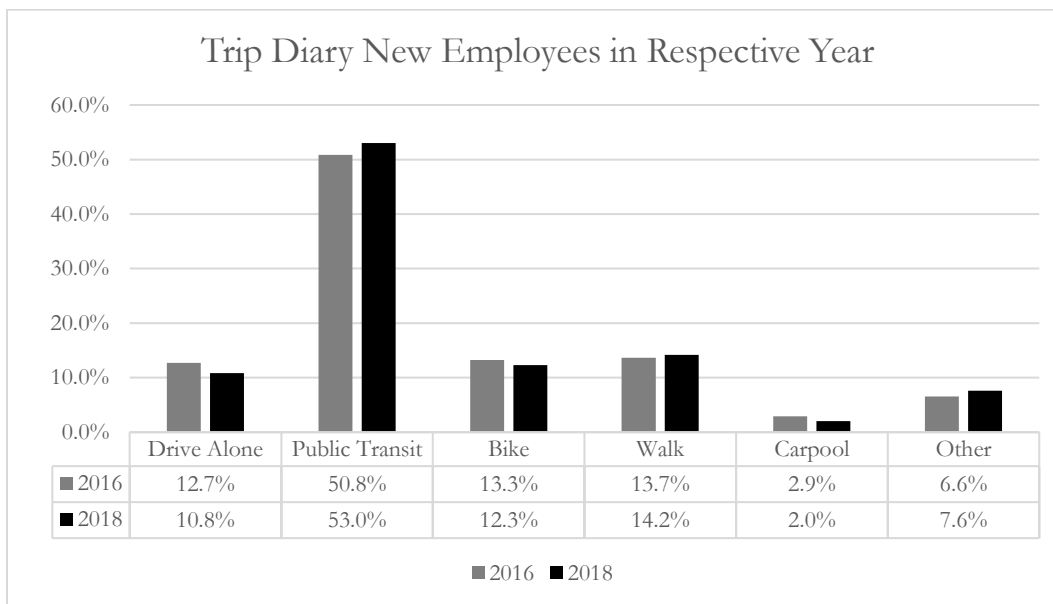


Figure C-11: Trip diary by new employees in each respective year

New employees tend to show a gradual decrease in public transit usage and an increase in driving alone the longer they stay at MIT. This is shown by following the modal trends from new employees who began between 2014 and 2016. The drive alone rate among these employees increased from 12% to 17% (both as a primary mode and in the trip diary – see Figure C-12 and Figure C-13). Public transportation rates dropped by about 1.5 percentage points over the two-year period. Cycling and walking both saw a decrease of about 2 percentage points over the two-year period. This matches the expected trend. However, it is important to note that the shift away from transit and towards driving is slow and not immediate.

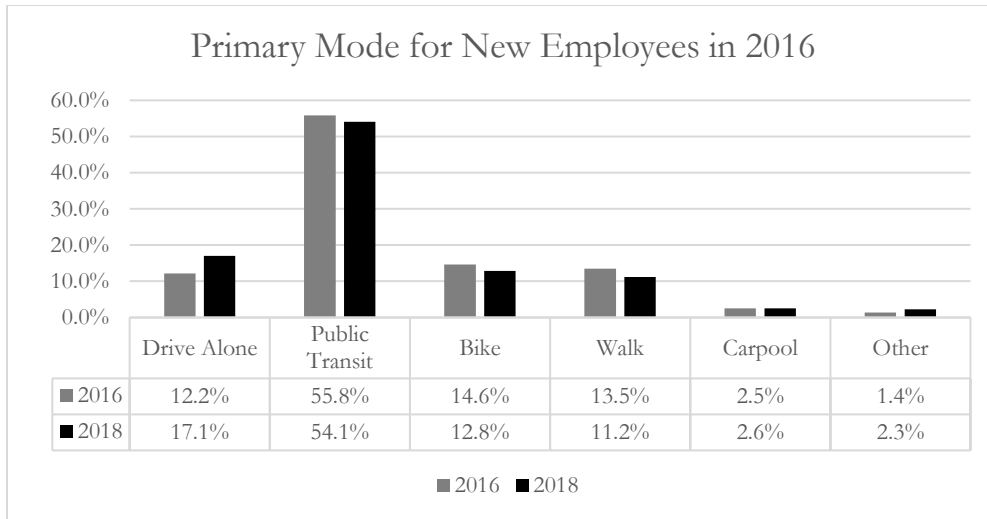


Figure C-12: Primary mode for employees who started at MIT between 2014 and 2016

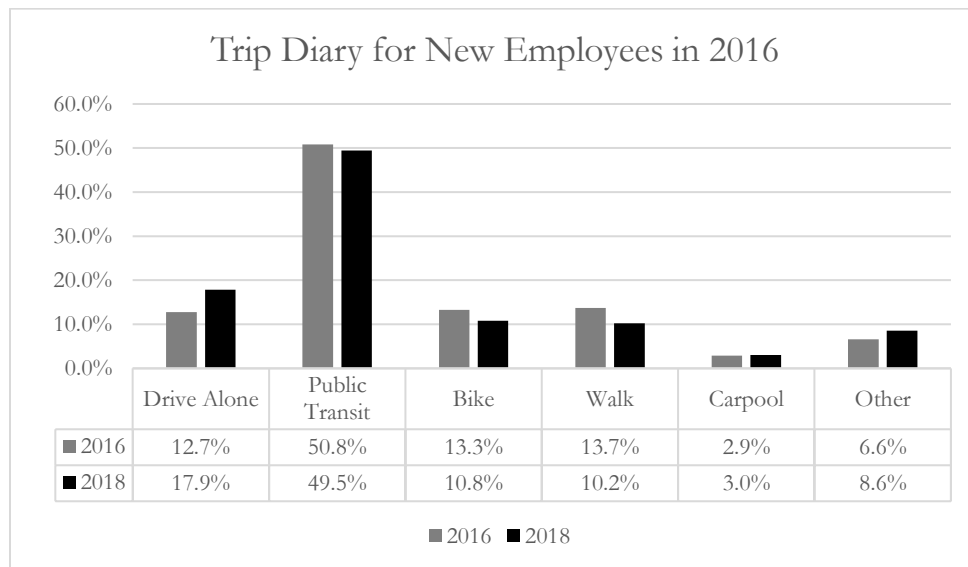


Figure C-13: Trip diary for employees who started at MIT between 2014 and 2016

As is consistent with the trip diary, the parking data for employees who started between 2014 and 2016 and who were still working in 2018 showed an increase in average days parked per week (0.41 to 0.57). However, the trip diary estimated a decrease in days per week riding transit (2.54 to 2.46) while the transit data showed an increase in transit use from 1.88 days per week to 2.00. Similar to other data trends, the trip diary overestimates the days taking each form of transportation per week. However, it is possible that this is due to missed data points as well. Ungated lots are not considered in the parking data and neither are commuter rail or EZ-Ride trips. Thus, it is possible the discrepancy is in part due to uncaptured driving or transit trips.

Table C-5: Parking and transit data for employees who started at MIT between 2014 and 2016

Avg Days / Week	2016-17	2017-18	2018-19
Transit Data	1.88	1.98	2.00
Transit Trip Diary	2.54	-	2.46
Parking Data	0.41	0.45	0.57
Parking Trip Diary	0.83	-	0.89

C.6 A Note on Data Sources and Discrepancies

There is often a discrepancy between the primary mode and the trip diary. This is partially due to people inaccurately stating their primary mode and partially due to the myth of the single mode commuter. Figure C-14 shows the relationship between the stated primary mode and the trip diary responses. For example, of the employees who said driving alone was their primary commute method, 85.8% of the trips they made in the trip diary were by driving alone. Those who indicated working from home as their primary mode took public transit for almost 25.2% of their trips. Transit makes up a significant portion of the trip diary for non-transit primary modes, such as those who primarily work from home (25.2%), take a TNC or Taxi (24.6%), bike (9.3%), walk (8.5%), or carpool (7.7%), yet it does not make up a large portion of those who primarily drive (2.8%).

Another interesting point is the higher rate of working from home among primary mode drivers than other modes (excluding TNC/Taxi). Those who primarily drive to work had a higher proportion of working from home days in the trip diary (8.2%) than those who primarily take public transportation (5.2%). As work-from-home is likely to persist after the end of the pandemic, it will be useful to follow which primary modes are most likely to work-from-home in the next commuter survey. While there are a lot of multi-modal preferences among all employees, the majority of trips (between 71% and 86%) are the same as the primary mode (excluding TNC/Taxi, work from home, and other).

Working from home, similar to taking transit, is also common in the trip diary among all primary modes. Working from home is most common among employees who primarily take TNC or taxi (14.4%) or drive to work (8.2%). There appear to be commonalities between driving, carpooling, and working from home. The three modes are rather high proportionally in their respective primary and trip diary responses. Another cluster appears between taking transit, walking, and biking. Those who walk and bike are likely to also take public transit. An important note is that the TNC, Work from Home, and Other primary modes accounted for only 1.9% of all employees, combined. This is to say that TNCs, WFH, and Other are more often than not a secondary mode rather than a primary commute method.

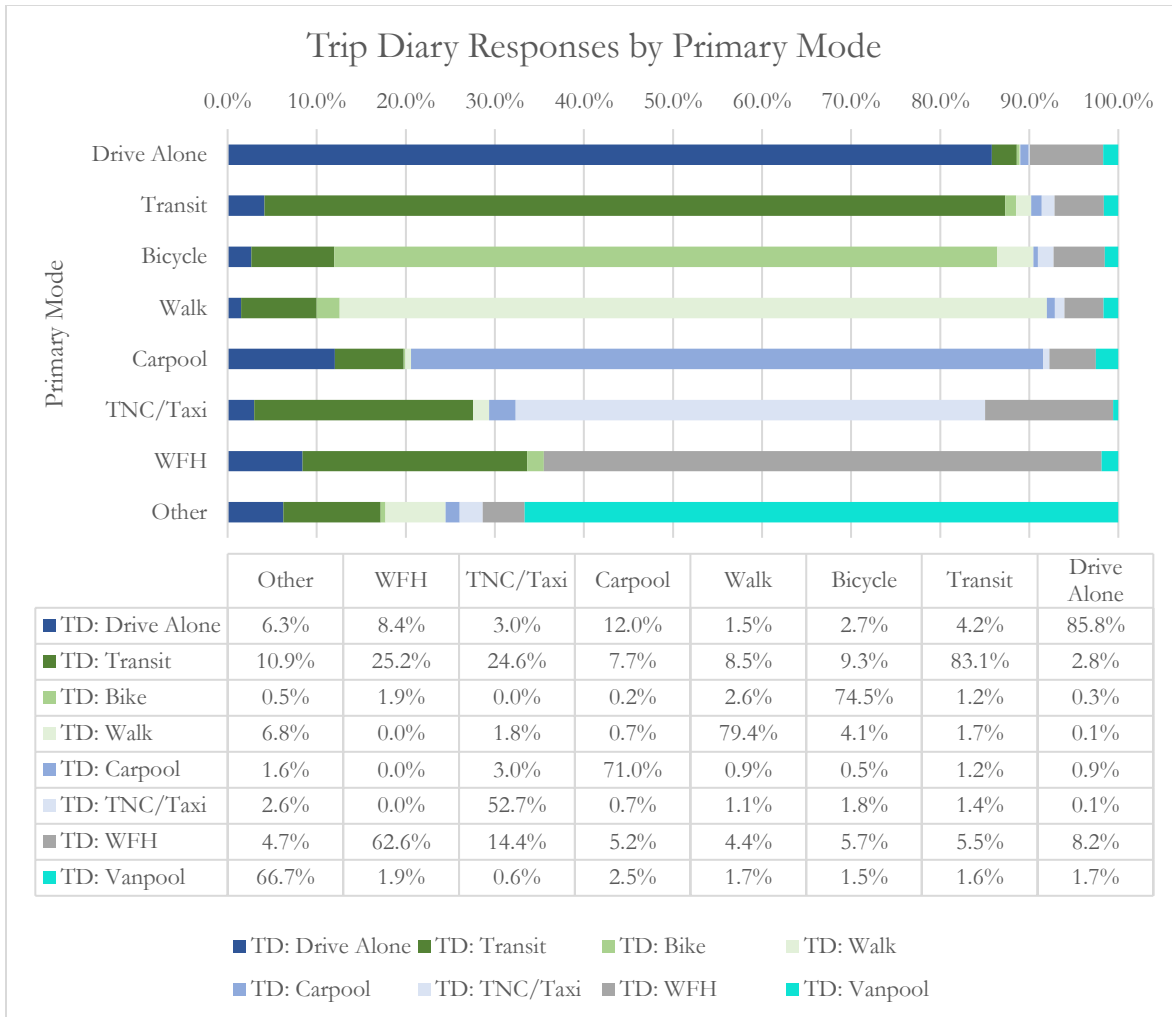


Figure C-14: Trip diary responses by the primary mode indicated by each respondent in the 2018 commuter survey

Another discrepancy is between the trip diary and the parking and transit data from MIT IDs. To make sure the data matched, only employees who answered the 2018 survey (N = 5660) are included in this analysis. The comparison is shown in Figure C-15 for drive alone and parking data and Figure C-16 for transit trip diary and MBTA tap data. The parking and MBTA tap data is from the full year compared to the trip diary. The parking data only looked at weekdays parked while the transit data used the full seven-day week. The trip diary shows a fairly consistent number of employees claiming to drive alone between one and five days per week, with a slightly higher spike at five days per week. The parking data shows a similar trend, although less likely to drive alone all five days. This makes sense since employees might take vacations, call in sick, need to take a different mode, or work from home and cannot drive to work every day for a full year. Additionally, 70.2% of employees did not claim to drive alone to campus any day on the trip diary and 69.2% of employees registered less than 0.5 days parking on campus per week.

Average Days Traveled to MIT per Week (Parking)

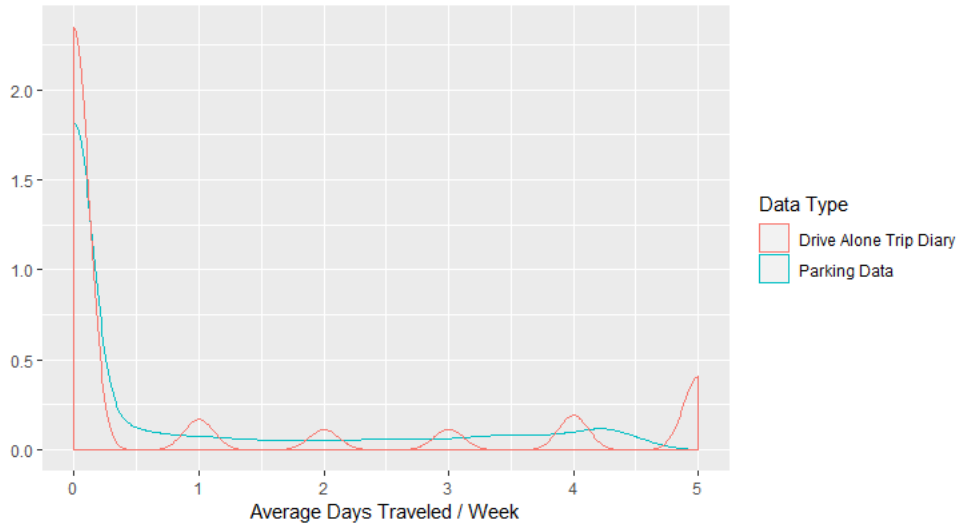


Figure C-15: Drive alone trip diary vs parking data per week

The transit data shows a slightly different picture, where employees were more likely to claim higher transit use in the trip diary (skews towards 5 days per week) compared to the actual data (fairly even between one and five days per week). Transit tends to be overcounted on the higher end (less employees likely to take transit 5 days per week on average) and undercounted on the lower end (more employees are likely to take transit between 1-3 days per week on average). Additionally, 45.8% of employees claimed to not use transit in the trip diary despite only 24.3% taking transit less than 0.5 times per week on average. This shows how the Mobility Pass has helped employees casually take transit and potentially pair it along with other modes (cycling or walking, primarily).

Average Days Traveled to MIT per Week (Transit)

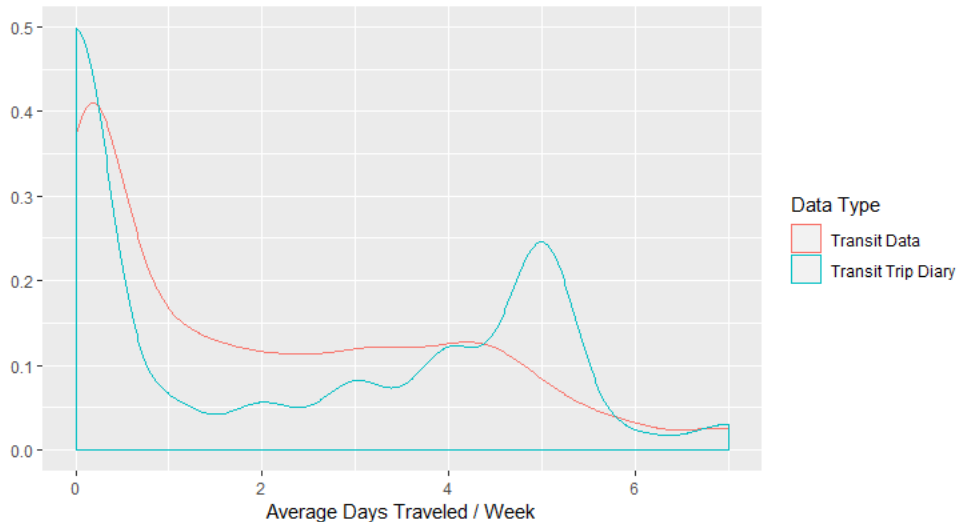


Figure C-16: Transit trip diary compared to MBTA tap data

Another way to compare the two is to take the difference between the trip diary responses and the actual weekly average tap data for each employee. These differences are plotted in Figure C-17. The plot only shows employees who either claimed to take public transit or drive alone at least once in the trip diary or who parked or took the MBTA more than 0.5 times on average each week, or both.

This removed employees who never parked/took transit and who never claimed to park/take transit (which would show up as 0 difference and skew the data around zero). Even still, there is a roughly normal distribution for each mode around zero, indicating employees are traveling similarly to their trip diary log. The mean for the parking difference was 0.59 and the mean for public transit was 0.22. Positive values indicate that employees claim to use a mode more on the trip diary than the revealed data indicates. The positive mean is likely due to certain transit and parking data not being collected (if they took commuter rail, EZ-Ride, or parked in an ungated lot).

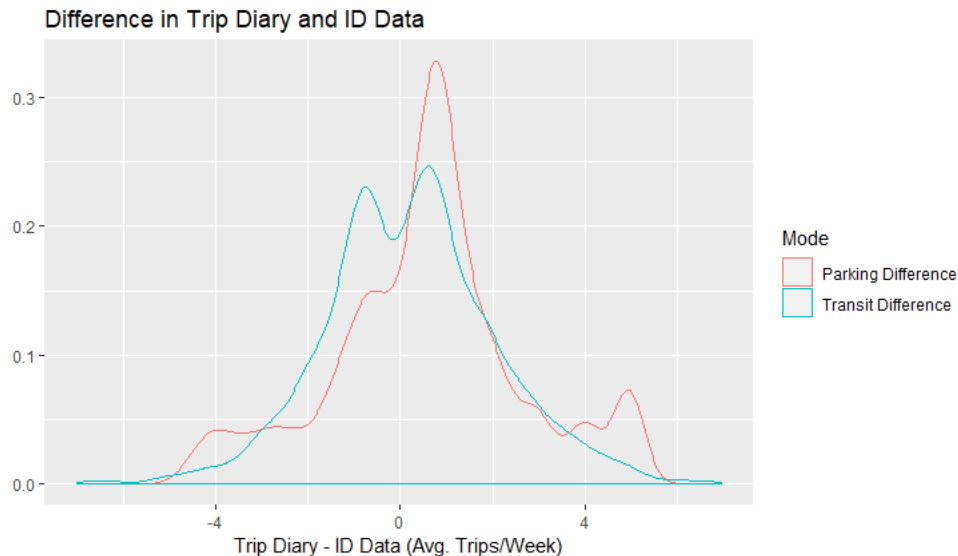


Figure C-17: Difference between trip diary and MIT ID tap data

Table C-6 and Table C-7 shows or tap data binned along the top (i.e. “0 – 0.5”, “0.5 – 1.5”, “1.5 – 2.5”, etc.) and the number of days traveled on transit or by driving alone on the rows. The percentages sum up to 100% along each row. As an example, of those who claimed to take transit 3 times in the prior week, 18.2% averaged between 1.5 and 2.5 trips per week and 17.4% averaged between 2.5 and 3.5 trips per week according to their tap data. One noticeable data point is the high proportion of employees who claim to have taken transit in the previous week but did not record any transit usage from their MIT ID (between 18.9% and 33.9% per trip diary response). This could be due to either falsely claiming they took transit or due to these employees taking non-MBTA bus or subway trips. For instance, if an employee claimed to take transit 4 times last week but did not record any transit use on their MIT ID, it could be due to them using Commuter Rail, EZ Ride, or the Wellesley Bus Exchange. Table C-6 also shows a diagonal trend, which suggests the trip diary responses were similar to the actual number of trips taken. However, the relationship is not sharp but blurred. For example, employees who indicated taking transit three days in the previous week had 11.8% take between 0.5 to 1.5 trips, 18.2% take between 1.5 and 2.5, 17.4% take 2.5 and 3.5, and 11.3% take between 3.5 and 4.5 trips per week. This shows a wide variety of actual average transit trips compared to the trip diary.

Table C-6: Transit trip diary (rows) vs MBTA taps from MIT IDs (columns) heatmap

TD\Data	No Transit Use	0-0.5	0.5-1.5	1.5-2.5	2.5-3.5	3.5-4.5	4.5-5.5	5.5+
0	29.3%	46.6%	14.1%	5.2%	2.7%	1.3%	0.5%	0.3%
1	22.3%	27.5%	19.4%	13.9%	9.5%	6.2%	0.7%	0.4%
2	26.3%	11.9%	15.1%	20.9%	14.0%	6.8%	4.3%	0.7%
3	29.7%	6.1%	11.8%	18.2%	17.4%	11.3%	2.9%	2.5%
4	33.9%	2.0%	7.6%	10.1%	18.7%	16.3%	8.2%	3.2%
5	32.0%	1.3%	4.3%	5.8%	11.5%	20.4%	15.6%	9.1%
6	18.9%	0.0%	5.6%	7.8%	7.8%	17.8%	13.3%	28.9%
7	26.9%	1.9%	5.1%	9.6%	7.1%	14.1%	15.4%	19.9%

The same heatmap was created with parking data, shown in Table C-7. Here, the relationship was a lot clearer between the stated (trip diary) and revealed (parking tap) data. For example, those who claimed to have driven alone twice in the trip diary, 31.4% parked between 1.5 and 2.5 times that year (and 32.5% between 0.5 and 1.5 times). For most of the trip diary responses, employees were similar in their average parking use. Similar to transit, but not as severe, there were roughly 11.5% to 23.3% of employees who reported driving alone to campus despite not showing parking data. This is likely due to employees who parked in non-gated or leased lots. The stronger correlation between the parking tap data and trip diary compared to transit could be in part due to the multi-modal options for transit users, walkers, and cyclists.

Table C-7: Drive alone trip diary (rows) vs parking taps from MIT IDs (columns) heatmap

TD\Data	No Parking Use	0-0.5	0.5-1.5	1.5-2.5	2.5-3.5	3.5-4.5	4.5-5
0	78.6%	10.7%	4.9%	1.4%	1.8%	2.2%	0.3%
1	23.3%	16.3%	33.7%	14.9%	6.6%	4.5%	0.7%
2	11.5%	3.1%	32.5%	31.4%	12.0%	9.4%	0.0%
3	13.9%	7.2%	14.9%	25.8%	21.1%	14.9%	2.1%
4	12.0%	4.6%	6.8%	13.5%	32.6%	29.2%	1.2%
5	12.8%	5.5%	4.9%	6.8%	18.0%	44.8%	7.1%

Since the trip diary only asked for one week of commuting history, comparing it to a full year's worth of transit and parking data has its faults. The commuter survey was distributed in October, so a more accurate comparison would be between the trip diary and parking and transit data for October 2018. Figure C-18 shows the difference between the trip diary and the MIT ID tap data for parking and transit using October 2018 data only. It shows a similar trend as Figure C-17, although the average difference between the trip diary and tap data is only 0.031 for parking and -0.094 for transit. This is significantly closer to zero than the full year dataset, which had a mean of 0.59 for parking and 0.22 for transit. Thus, the October data lines up closer to the trip diary than the yearly data, as would be expected. However, it is useful to check the comparison from the trip diary to the yearly data to ensure the trip diary can be used as an estimate of the yearly data.

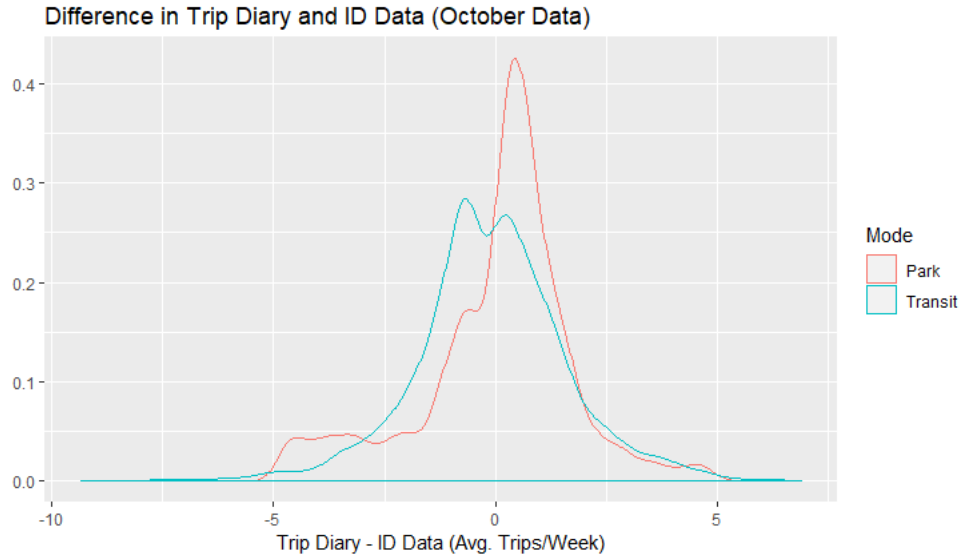


Figure C-18: Difference between trip diary and MIT ID tap data (October 2018)

Overall, the trip diary appears to align fairly well with the revealed tap data in aggregate but is less accurate on a disaggregate level. The difference between stated and revealed data is near-zero, albeit slightly higher in the trip diary. The parking data per week aligns closer to the trip diary (Table C-7) on a disaggregate level. The trip diary appears to overcount the higher transit users (5+ days taking transit) and undercount the moderate transit users (1-3 days taking transit), as shown in Figure C-16. In aggregate, the employees who stated higher transit and parking use than they actual revealed were counteracted by the employees who undercounted their transit and parking usage. The trip diary can be used to indicate the average number of days employees take each mode to campus, albeit with the caveat that it will likely overcount the values slightly.

Finally, the primary mode indication was compared to transit and parking tap data. Figure C-19 shows the distribution of MBTA tap data for users who indicated public transit as their primary mode and those who did not. As expected, those who claimed to take public transit had a higher rate of transit usage than those who listed another mode as their primary. The average days taking transit per week was 3.45 for those who had public transit as their primary mode and 0.74 for those who didn't (2.05 average across both sets of employees). Similar to the trip diary comparison, there is a large cohort of employees who put public transit as their primary mode yet do not show any tap data. This could be due to falsely claiming they take transit or it could be that they take non-MBTA transit trips or commuter rail trips (i.e. EZ Ride, Wellesley Exchange Bus, etc.). Those employees who did not indicate transit as their primary mode but still took transit show the benefit of the Mobility Pass. Employees are able to occasionally or infrequently take transit even when they normally take another mode to campus.

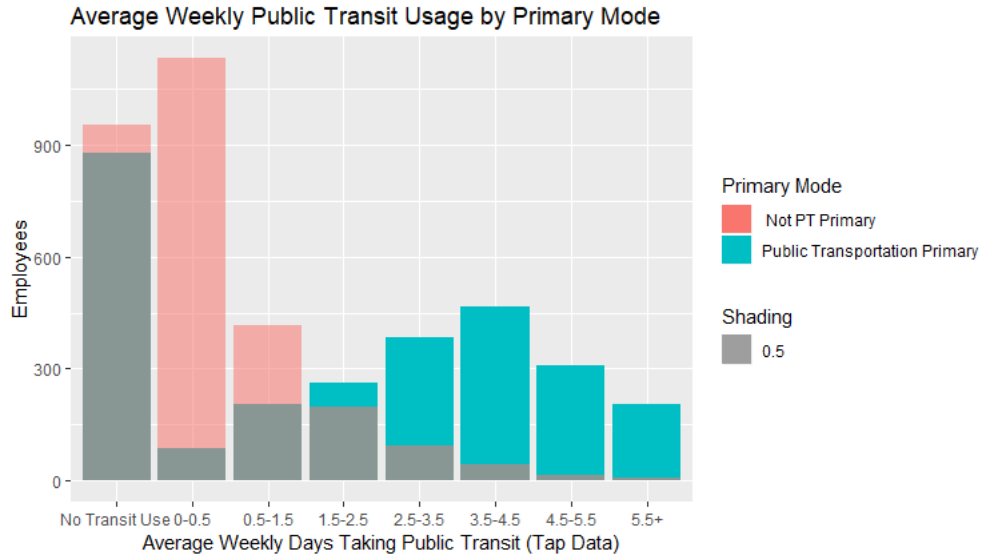


Figure C-19: Public transit usage by primary mode indication

A similar trend is shown with those who indicated driving alone as their primary mode (Figure C-20). Those who indicated primarily driving alone to work had an average of 2.61 days driving alone to work whereas those who indicated another primary mode had an average of 0.30 days driving alone to work (0.85 was the employee average). There was a smaller portion of employees who indicated driving alone primarily but did not register any tap data. These employees might either be falsely claiming they drive to work or, most likely they are parking in non-gated lots or leased lots. Overall, the primary mode does indicate a higher likelihood of using that mode of transportation but does not guarantee that those employees will use it more than other employees. Additionally, there are still employees who indicate primarily taking another mode but are still parking on campus a few days per week on average. Some of these are likely from carpool commuters, where the driver of the carpool would be captured parking on campus.

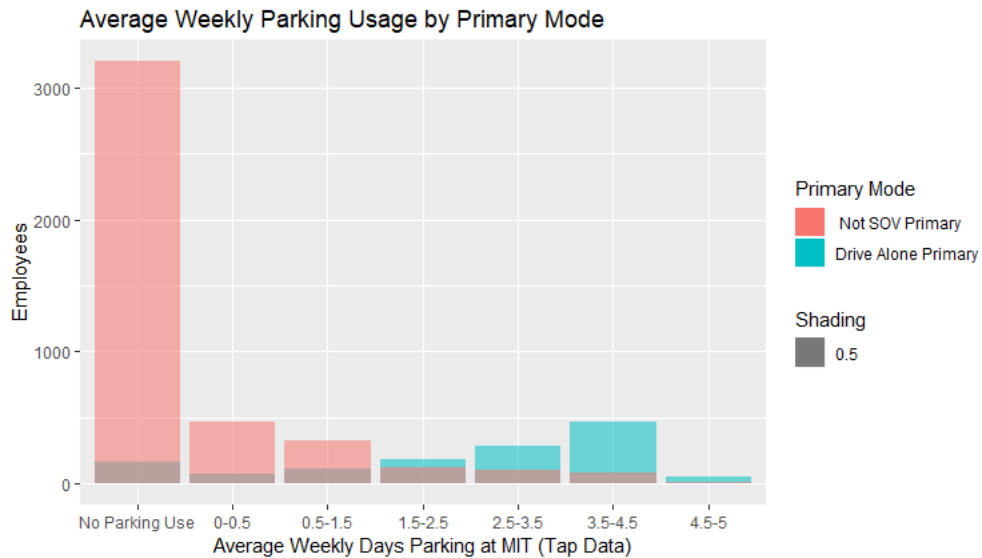


Figure C-20: Days parking on campus by primary mode indication

C.7 The Multi-Modal Employee

It is often assumed that people stick with one mode of transportation when they commute. However, in cities with multiple available modes of transportation, employees have options in how they commute to work. With trip chaining as well, some modes of transportation might be more efficient on some days compared to others. For example, if an employee plans on picking up their child from school after work, they might choose to take transit if the school is near a transit route. On days they aren't picking up their child, they might bike to work instead. This analysis focuses on exploring the multi-modal tendencies of MIT employees. It relies mostly on the trip diary but also uses the MIT ID tap data to add substance and only looks at the 2018-19 academic year (most recent full data available). Based on the trip diary, 27.2% of employees claimed to take more than one mode to campus (not including working from home). The vast majority of these took just two modes, but a few took three or more modes in the trip diary (see Figure C-21 **Error! Reference source not found.**).

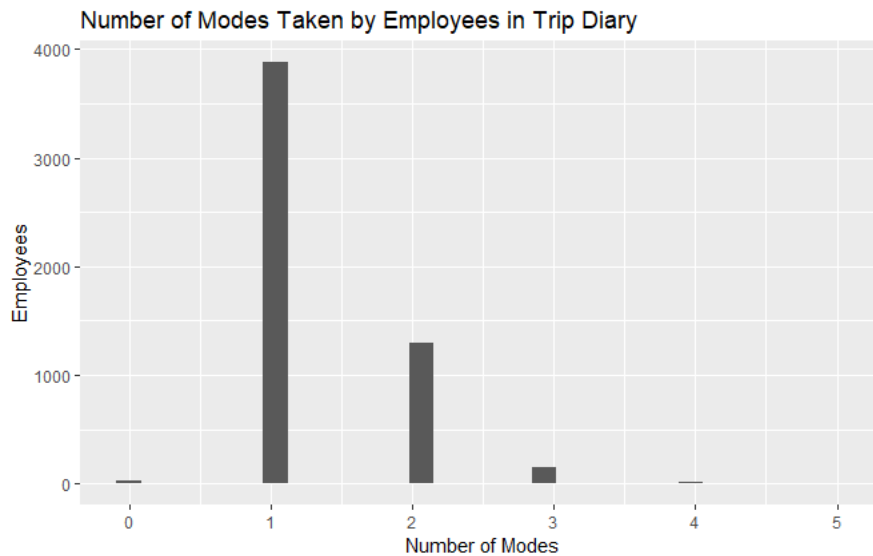


Figure C-21: Number of modes taken by employees in the trip diary (zero indicates they only worked from home)

Figure C-22 shows a boxplot of the average weekly days parked and traveled to campus on transit grouped by the most common trip diary response. This grouping was done to better compare the trip diary with the tap data, since the trip diary can better show multi-modal tendencies by employees than the primary mode. As is expected, those who claimed to mostly drive or take transit in the trip diary saw the highest proportion of employees parking or taking transit, respectively. Carpool had the next highest proportion of parkers, likely due to some of them being the driver of the carpool and also potentially to them driving alone some days. Biking and walking had a sizeable transit usage cohort, which suggests they take the T on occasion. Interestingly, the TNC/Taxi users have a relatively high transit usage and minimal parking.

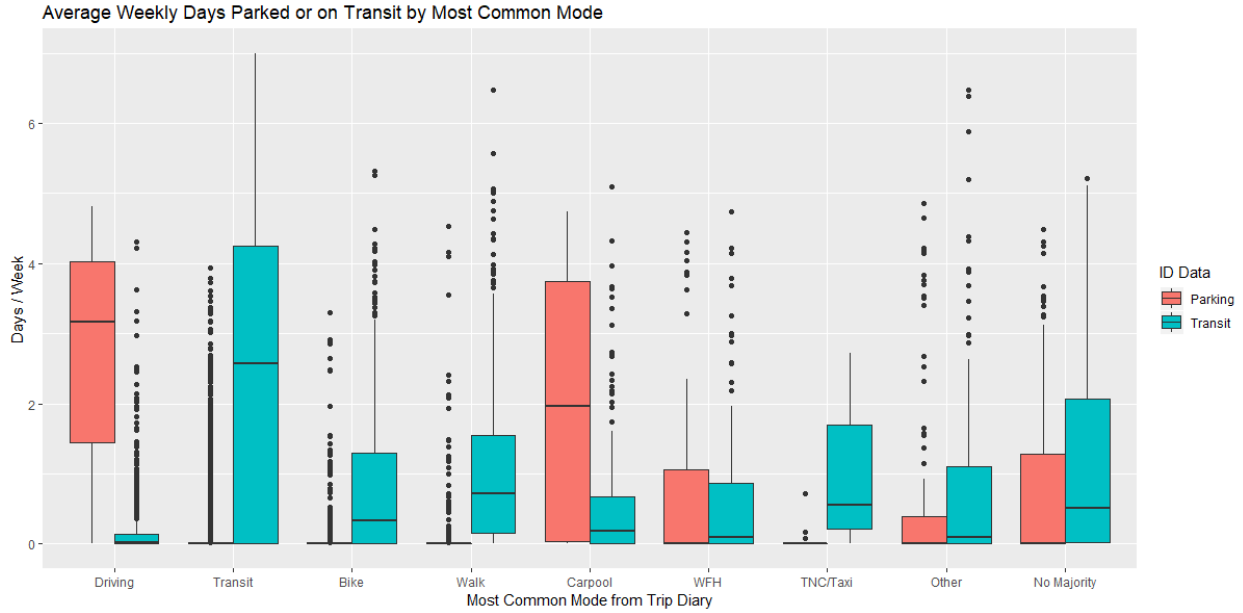


Figure C-22: Boxplots of parking and transit tap data by the most commonly indicated mode in the trip diary

Table C-8 shows the average days per week that employees parked and took transit, as well as the average number of licenses and autos per household for MIT employees grouped by the most commonly indicated mode in the trip diary. As anticipated, those who drive or commute in a carpool have the highest average days per week they parked on campus. Those who primarily took transit, walked, took a TNC or taxi, or cycled had the highest average days per week taking transit. In fact, those who primarily walked had an average of 1.06 days taking transit per week. Those who walked also have the lowest number of licenses and vehicles per employee household as well. Employees who primarily took public transit in the trip diary had a higher number of licenses and autos per household than those who biked, walked, or took a TNC/taxi to campus. This could be in part because transit includes a greater reach than biking or walking. For example, many employees who take the MBTA might live in the suburbs and take commuter rail. Many commuter rail riders drive to the stations since the density around stations is low. These commuters still take public transit, but also own vehicles and use them to access transit.

Table C-8: Average days parking or taking transit to MIT and average licenses and available autos per household by the most commonly indicated mode in the trip diary

Majority TD	Parking	Transit	Licenses	Autos
Drive Alone	2.67	0.16	2.05	2.02
Public Transportation	0.17	2.46	1.81	1.27
Bicycle	0.13	0.81	1.76	0.86
Walk	0.11	1.06	1.46	0.63
Carpool	1.99	0.58	2.20	1.78
Work from home	0.74	0.70	1.91	1.60
TNC/Taxi	0.03	0.85	1.50	0.72
Other	0.67	0.96	1.87	1.54
No Majority	0.72	1.13	1.85	1.37

Between drivers and transit users, there were 8.9% of employees who indicated taking transit and driving to MIT at least one day in the trip diary. Out of the same portion of employees who answered the survey, there were 6.3% who had an average of at least 0.5 days / week on transit or parking on campus. While these two values do not line up nicely, the tap data does not include commuter rail users and employees who park in lots or leased spots off-campus. This could partially explain why the trip diary combination of driving and transit is higher than the actual tap data. Regardless, even among transit and driving, there are a sizable number of employees who switch between transit and driving to campus.

Table C-9 shows the number of modes selected in the trip diary by primary mode. Of those who selected driving alone as their primary mode, only 13.3% indicated taking more than one mode on the trip diary. Those who indicate that they primarily drive or work from home are most likely to only take one mode (not including working from home) to campus. Note that since working from home is not considered a mode taken to campus, all of the work-from-home primary mode employees shown are those who take at least one other mode to campus. Almost a quarter of public transportation users take more than one mode to campus. The most multi-modal employees are cyclists, carpoolers, walkers, and those in the ‘Other’ category, all with 30-40% of them taking more than one mode. Very few take more than two modes, with TNC/taxi users most likely to do so at 9.4%.

Table C-9: Number of modes taken in the trip diary by primary mode

Primary\N modes	1	2	3	4	5
Drive Alone	86.7%	12.4%	0.9%	0.0%	0.0%
Public Transportation	73.4%	24.2%	2.2%	0.1%	0.0%
Bicycle	54.0%	37.5%	7.0%	1.3%	0.2%
Walk	61.8%	32.5%	5.1%	0.6%	0.0%
Carpool	55.3%	40.2%	4.5%	0.0%	0.0%
Work from home	85.7%	14.3%	0.0%	0.0%	0.0%
TNC/Taxi	65.6%	25.0%	9.4%	0.0%	0.0%
Other	54.1%	35.1%	8.1%	2.7%	0.0%

Table C-10 takes a closer look at the other modes taken for each primary mode. The right-most column indicates the percent of employees who only indicated one mode in the trip diary (the same as the primary mode). The other columns indicate the percent of employees who also indicated that other mode in their trip diary. For example, 86.7% of employees who claimed to primarily drive alone only indicated one mode in the trip diary and 8.7% of those employees also indicated taking transit at least once. The rows do not add up to 100% since each employee could indicate multiple modes in their trip diary. Interestingly, people who primarily drive are more likely to take transit than any other mode and vice-versa. Walking, cycling, and taking a TNC or taxi are less likely to be mono-modal (between 54-66%) and most likely to also take transit as a secondary mode (between 23-41%). Those who primarily carpool are most likely to also drive alone to campus (30.7%) but also likely to take transit (18.9%).

Table C-10: Other modes taken in the trip diary by primary mode

Primary\TD	Drive Alone	Transit	Bike	Walk	Carpool	Taxi	Other	Mono-modal
Drive Alone	-	8.7%	0.9%	0.2%	2.6%	0.5%	3.0%	86.7%
Transit	13.7%	-	2.8%	4.5%	3.9%	4.6%	2.9%	73.4%
Bike	9.8%	26.7%	-	12.5%	2.3%	6.3%	3.8%	54.0%
Walk	5.5%	23.4%	8.3%	-	3.6%	4.2%	4.4%	61.8%
Carpool	30.7%	18.9%	0.8%	1.6%	-	2.5%	4.5%	55.3%
Taxi	9.4%	40.6%	0.0%	9.4%	9.4%	-	3.1%	65.6%
Other	24.3%	16.2%	2.7%	13.5%	5.4%	8.1%	-	54.1%

Appendix D: Scaling the Employer Panel Survey

With a small sample that is likely skewed towards larger employers, the question of scaling the results and accounting for sampling bias is a primary consideration in interpreting the Employer Panel Survey results. The goal of the scaling method presented here is to get reasonably representative results for all employees in the MBTA service area, not necessarily all companies, so that one can infer potential ridership return among the various employer policy impacts on ridership. The following discussion outlines the approach used in scaling the December 2020 Employer Panel Survey.

The basic assumption is to scale based on the information available from all Perq participating employers. In the May 2019 Corporate Program Survey, the survey was scaled based on all employers in the Perq program. This worked well since the survey respondents had similar employer size and location distributions as the overall Perq employer distributions. In addition, the only unknowns were the employer and employees who obtained transit benefits via third-party providers (i.e. WageWorks, Edenred, etc.). Data from these 3rd-party providers are an agglomeration of many companies receiving transportation pre-tax benefits through their payroll services. The make-up of these employers is assumed to be similar to that of Perq. The December 2020 Employer Panel Survey, however, only had 68% of respondents listed as Perq members. Since a large portion of these employers are not in Perq, their decisions on transportation benefits might not be comparable to Perq employers, who have already shown an interest in providing a public transit benefit (in the form of pre-tax payroll deductions or at least having a portal through the MBTA) by enrolling in Perq. However, these non-Perq employers are most likely to be using 3rd-party providers and/or have similar transportation benefits as Perq companies, based on the fact that the overwhelming majority of the employees represented in the December surveyed companies had transportation payroll deduction benefits. Also, since these non-Perq employers took the initiative to respond to a survey promoted by the MBTA, it is assumed they have interest in MBTA transportation benefits and are similar to Perq employers.

The population of interest are employers within the MBTA service area who offer transportation benefits, even if only a pre-tax payroll deduction. The MBTA is not likely interested in the employers in all of Greater Boston, but rather the employers most likely to use their system, which tend to be concentrated in the core area. These employers are more likely to be similar in distribution to Perq members, since Perq members are more likely to be near transit and offer transit benefits (due to self-selection into Perq). For that reason, the population of interest to the MBTA is most similar in distribution to Perq employers, who are likely located near MBTA stations and stops. The assumption is that non-Perq employers who responded to the December 2020 Survey (32% of respondents) are similar to Perq members in their location and transit proximity. The best estimate of the employer size distribution for Perq-like employers is from the May 2019 Corporate Program Survey, which had a 25% response rate and similar size and location distributions as all Perq participants.

However, employer size distribution, based on number of employees, is not known for all of Perq. Instead, the number of MBTA passes ordered per employer is used as a proxy of employer size. To get a comparable distribution between the December 2020 EPS and Perq employers, it is necessary to estimate the number of passholders pre-COVID for the December 2020 EPS respondents. A

question on the survey asked employers to indicate how many employees utilized the pre-tax payroll deductions, but not every employer responded to this question and it specifically asked for the number as of December 2020. Table D-1 shows the proportion of passholders per employer, grouped by employer size (based on number of employees), from the May 2019 Corporate Program Survey (CPS). The general trend is for larger employers to have a smaller share of employees taking transit. This may be due to self-selection of smaller employers in Perq having higher interest in MBTA passes. The weighted average percent of employees ordering MBTA passes through Perq are applied to the December 2020 respondents by employment size. This provides an estimate on the number of passes ordered per company and respondent and can then be used to re-group the sizes to match the May 2019 CPS and Perq employer size distributions from previous analyses.

Table D-1: Percent of employees ordering passes by employer size (May 2019 CPS)

Size	Passes Ordered	Employees	% Passes
0 - 19	612	1175	52.1%
20 - 99	2553	5697	44.8%
100 - 249	1593	3851	41.4%
250 - 999	1870	5173	36.1%
1000 +	32691	110054	29.7%

Table D-2 shows the size distribution of the December 2020 EPS after applying the estimated pass distribution among employers. The table also includes the May 2019 CPS card distribution and Perq distribution in May 2019, not including 3rd-party providers. While the number of employers in each size distribution match between the May 2019 CPS and overall Perq, the responses had a slight skew towards the largest employers (which were very few in terms of number of companies), which due to their large employee-base, skews the number of cards ordered by the employers. The next step is to scale up the number of cards from the December 2020 EPS to the May 2019 CPS, and again to the total Perq population based on the size categories. This provides an estimate on the percent of passholders in Perq affected by employer responses to the December 2020 EPS. To get an estimate on the number of employees affected, a reverse of Table D-2 **Error! Reference source not found.** is applied, where the estimated number of passholders is divided by the percent of employees who ordered passes.

Table D-2: Number and percent of cards in each size group per survey and Perq population

Cards Ordered	December 2020 EPS		May 2019 CPS		Perq in May 2019	
	Cards	% Cards	Cards	% Cards	Cards	% Cards
0 - 9	79.9	0.5%	687	1.6%	2685	3.3%
10 - 24	206.1	1.2%	1451	3.4%	4872	6.0%
25 - 49	188.9	1.1%	1864	4.3%	6816	8.3%
50 - 99	403.7	2.3%	1722	4.0%	6226	7.6%
100 - 999	3902.3	22.4%	5844	13.6%	20094	24.6%
1000 +	12655.7	72.6%	31426	73.1%	53730	50.2%

The final step is to estimate the total number of passholders that are in companies not through Perq. This primarily consists of employers working with the 3rd-party providers and retail MBTA pass sales not captured on Perq. The assumption is that the size distribution of the employers who work with 3rd-party providers and those who are in neither, but whose employees purchase monthly passes

through the retail channels, are similar to the size distributions in Perq. Thus, the distribution of employees by employer size will not change. Applying this estimate, however, can help understand how many passholders throughout the MBTA bus and subway system are offered transit subsidies. This will be useful in applying a scenario analysis on Perq and non-Perq employers who may be interested in opting in to the Mobility Pass.

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