



Human-Centric Mobility: Exploring Non-Work Travel Patterns in D.C.

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Human-Centric Mobility: Exploring Non-Work Travel Patterns in D.C.

A DISSERTATION PRESENTED

BY

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TO

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Human-Centric Mobility: Exploring Non-Work Travel Patterns in D.C.

ABSTRACT

Public transportation in the U.S. has been designed to serve worker travel patterns. However, only 18% of urban mobility trips are for the purpose of work³³. Further, post-pandemic, the proportion of trips taken for the purpose of work is decreasing. In order to boost ridership and more equitably serve their communities, public transportation agencies need to consider non-work travel patterns. Using mobile phone data and tap-in/tap-out public transportation data from D.C., this thesis explores the convenience disparities and changes in demand for non-work travel patterns on public transportation. We found that approximately 10% more trips are for the purpose of travelling from the home to a non-work destination post-pandemic compared to pre-pandemic. We found there is a significant convenience burden for non-work trips on public transportation. Non-work trips take 85% longer in travel time and are 55% slower in travel speed than work trips.

This project is in collaboration with the Washington Metropolitan Area Transit Authority (WMATA).

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1

Introduction

PUBLIC TRANSPORTATION* IS AN ESSENTIAL SERVICE that supports urban and suburban residents throughout their daily tasks in many cities across the globe. Where public transportation

*Public transportation is defined as a high capacity transportation system that collects fares to run on fixed routes. This includes, but is not limited to, subways, buses, commuter rail, and street trams. Public Transportation does not include ride-shares, taxis, private vehicles, or aviation. Throughout this thesis, we will be focusing on the urban environment

is successful, it offers people a convenient, affordable, fast, and direct route to their destinations. However, in the US, taking public transportation is distinctly less convenient than driving a car for the purpose of daily tasks³³. One reason is that American public transportation systems are predominantly designed to facilitate transportation between home and work, as opposed to other daily tasks such as grocery shopping, dropping off children, or seeing friends⁴⁴. Work-related trips, however, only make up a small and decreasing percentage of overall transit demand in post-pandemic America³³. Further, work-related trips are less likely to be performed by low-income Americans, who must choose between using unreliable public transportation to serve their other daily needs⁵⁰, or spending significant portions of their income on a private vehicle¹³.

Effective public transit could lift the burden of prohibitively expensive and unreliable mobility on millions of Americans¹⁷. This outcome is achievable if agencies plan better for non-work travel^{55 27}. However, planning efforts are hindered by a dearth of existing studies on non-work urban travel patterns. The few that do exist rely on limited and potentially biased survey data and/or focus on only a specific demographic[†].

In pursuit of exploring another vision for public transportation that doesn't focus on the worker, the goal of this thesis is to better understand non-work travel patterns on public transportation. We use mobile phone data and public transportation data in D.C. to explore the following research questions:

- Has the public transportation demand for non-work-related travel in the D.C. metropolitan area changed between 2019 and 2022?
- Are there disparities in convenience on public transportation between non-work- and work-related travel?

The data was provided from a partnership with Washington Metropolitan Area Transit Author-

[†]See Chapter 2 (Background)

ity (WMATA).

The overall challenge is, **how can we more effectively design public transportation systems to better serve non-work mobility needs?**

1.1 DISPARITIES IN CONVENIENCE ON PUBLIC TRANSIT BY TRIP PURPOSE

People primarily travel for non-work purposes. Only 18% of the time people left their house in 2017 was for the purpose of work using any mode of travel, including private vehicle or public transportation³³. However, in the US, evidence suggests that it is notably less convenient to travel for non-work on public transportation^{26 27} than work trips. Despite non-work destinations being typically closer than work destinations and taking on average 13% less time to arrive in the car, taking public transit for non-work trips took *longer*³³ than work trips. A successful public transportation system would proportionately serve all types of travel purposes and focus on improving the travel experience for the majority of its ridership base.

However, a disproportionate number of people are choosing not to use public transportation to serve these non-work travel patterns, potentially due to the worse convenience. This disparity in convenience on public transportation by trip purpose translates into the proportions of people using public transportation for non-work purposes. The National Household Travel Survey - the main, U.S. wide, Bureau of Transportation commissioned survey - is a survey of randomly sampled Americans (over 120k in 2017)³³ from several metropolitan areas across the United States. Using the results from this survey in 2017 and 2022, we are able to get a general picture of travel patterns across the US. First, we see that people mostly travel for non-work purposes. In 2017, only 18% of all trips in the U.S. were commute (work) trips. Family trips, socializing, and shopping made up 30%, 29%, and 20% respectively. However, the travel demand picture looks different when we look at just public transportation trips. People disproportionately used public transportation for work.

38% of public transportation trips were used to get to work, more than double the proportion of all trips³³ (See Figure 1.1)

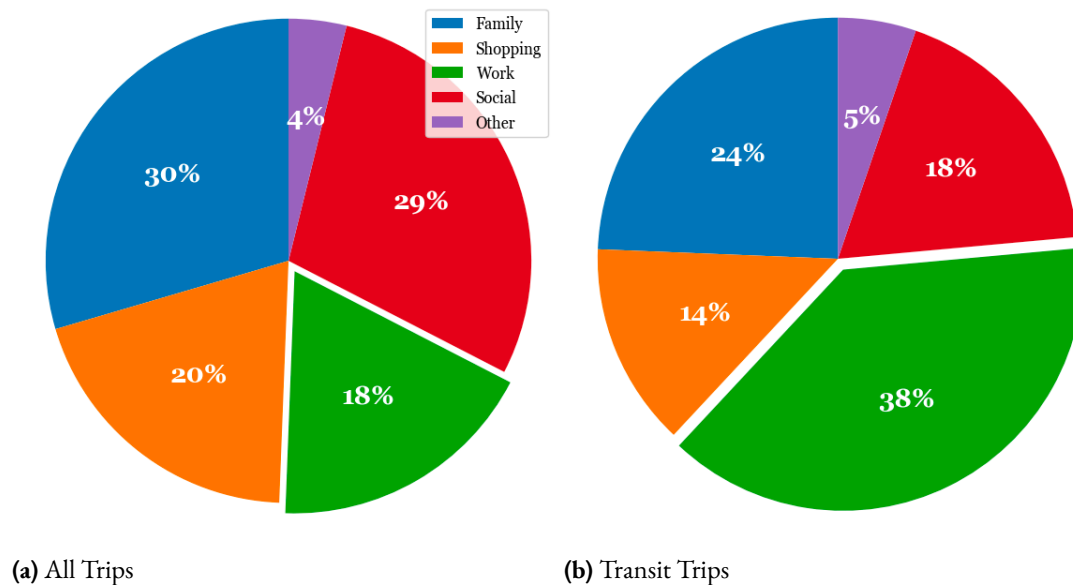


Figure 1.1: 2017 NHTS Trip Purpose By Mode³³

The picture is even more drastic in the D.C. metropolitan area. According to the NHTS, in D.C. in 2017, although only 25% of all trips were for the purpose of commuting to work, 80% of all trips on public transportation were for that purpose¹. People who are travelling for work are more likely to choose public transportation as their mode of choice than people not travelling for work. This demonstrates that public transportation disproportionately serves workers in D.C. With work trips dominating transportation usage disproportionately, there is an opportunity for public transportation agencies to offer services that are more representative residents' mobility needs.

Recent trends since the COVID pandemic have pointed to a lower proportion of trips on public transportation being made for the purpose of work^{24 34}. The NHTS findings showed that while in 2017, nationally, 38% of public transportation trips were made for work, in 2022, the percentage dropped to 33%³⁴. More people have been working from home²⁴, contributing to a lower demand

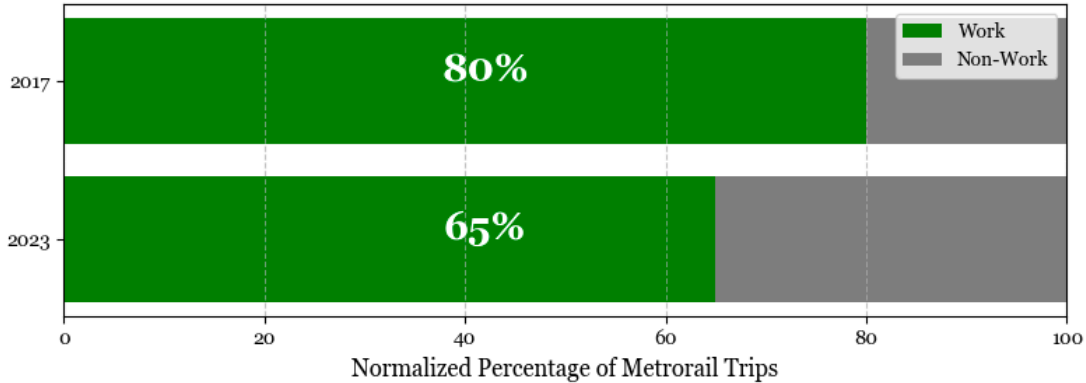


Figure 1.2: D.C. Metrorail Trip Purpose Pre- vs. Post- Pandemic⁶⁴

for work-related travel. The trend is further pronounced in post-pandemic D.C. In Spring 2023, 65% of Metrorail trips were to or from work, compared to 80% before the pandemic, dropping 15 percentage points⁶⁴ (see Figure 1.2).

Given that travel behavior differs by travel purpose, we see that demands of public transportation riders are changing towards more non-work travel behavior. Since people travelling for non-work purposes are more likely to travel off-peak, there is increased demand for travel in the middle of the day and during the weekends. We indeed see this change empirically. D.C. Peak ridership in 2019 was approximately 4 times the ridership midday, while in 2022, the peaks are only 1.5 times the midday ridership⁵⁵ (see Figure 1.3). The peak demands are flattening. Overall, a larger share of individuals are travelling for the purpose of non-work, and thus, are travelling proportionately more during off-peak hours than pre-pandemic.

Further, there is a group of *transit-dependent* people that rely on transit to serve all of their travel needs¹⁷. These people include lower-income folks, elderly, disabled individuals, and youth (including college-age youth). As these people are travelling more for non-work purposes, their travel behavior is more off-peak and intra-city, which is less supported by agencies across the country¹⁷. Regardless of the quality of public service, these people will continue to use public transportation.

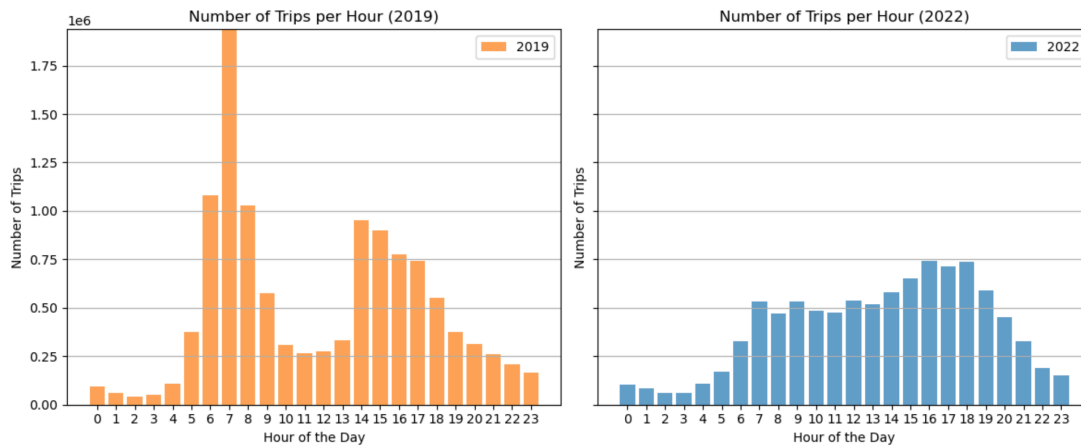


Figure 1.3: Weekday Trip Demand by Time of Day⁶

And the service is not designed optimally for even the people that have no other option but to use the public service. This introduces a moral alternative to design public transportation not just to boost ridership, but also to better serve those already riding.

Designing a service that better meets the demands of both riders and non-riders is an important step to increase ridership. Existing riders who have an easier time arriving to their destination may choose to use transit more. Further, non-riders may find that if transit serves their needs better than other modes of travel, they may choose to take public transportation.

Overall, public transportation agencies have an opportunity to better serve the diverse mobility needs of their communities. By observing the array of travel purposes and the associated travel behavior, we can better inform public transportation agencies on how to design for the post-pandemic travel demand trends. Further, we can inform transit agencies on how to better serve the marginalized communities on their system.

1.2 DESIGNING FOR NON-WORK URBAN TRAVEL IN THE U.S.

Why does public transportation disproportionately serve the worker? Part of the reason is that American public transportation systems are designed primarily for the types of travel patterns that distinctly serve commuter travel patterns^{60, 26}. Prioritizing service for workers specifically means prioritizing convenience for people travelling into the city in the morning and out of the city in the evening. Public transportation systems with a worker-centric design tend to exhibit the following two characteristics:

- More frequent service during peak hours and less frequent service during middle of the day and weekends⁶⁰
- Routes designed to bring people into and out of the central business districts²⁶

Unfortunately, these system characteristics are less useful for people travelling for other purposes. For example, let's observe a person travelling for the purpose of a medical appointment in the middle of the day who may need to come from work to another place in the city. This person's travel behavior would be off-peak, in the middle of the day, and would need to move from one part of the city to another, without going in and out of the city. Let's posit specifically how agencies can serve these different travel patterns.

"Better" service is measured by a specific set of metrics. Agencies pay attention to the following characteristics in their planning process:

- **Ridership:** Ridership is the total number of trips taken by a system. There are two components to ridership: 1) the number of people who choose to take transit; 2) the number of trips taken per person on transit. Ridership increases when more people choose to take the system regularly[‡].

[‡]Many transit agency revenues rely heavily on fares to cover their operational costs¹⁹. Approximately

- **Travel Time:** Agencies work to decrease the travel time (including wait times) between an origin and destination.
- **Wait times:** The wait times of riders include both the time waiting for a vehicle to arrive at the beginning of the journey and the transfer wait time.
- **Connectivity:** Connectivity gauges the ease with which riders access the transit system from their starting point and reach their intended destination.
- **Reliability:** The rate at which vehicles arrive at the stop at the scheduled time. This is an important metric because people would be more inclined to choose their transit option if they know it will drop them off at the expected time.
- **Equity:** Lower-income and other marginalized communities that are more likely to be transit-dependent are considered. Accessibility is an important part of equity. Agencies consider accessibility and equity in their planning.
- **Comfort & Safety:** Perceived lack of safety is an important reason people choose other modes of travel, particularly women²⁰. Crowding, largely during peak hours, as well as cleanliness, contributes to riders' discomfort.

This thesis will focus on ridership, travel time, wait times, and equity. While acknowledging the significance of other metrics, they might prove more challenging to influence through the levers within the control of transportation agencies.

In order to make progress along these metrics, agencies can control the following aspects of the system. By adjusting these levers, public transit agencies respond to changes in their rider travel demands.

38% of D.C.'s operating budget was from fares in 2019⁶³. In order to cover their operating costs, agencies are incentivized to increase their ridership.

- **Location of Stops:** Which areas get served contributes to connectivity of the system. However, too many stops can increase the travel time and introduce more variance in reliability.
- **Route Designs:** Agencies decide which routes serve which stops. This influences the travel time between points of interest, connectivity, and ridership.
- **Route Frequencies:** More frequent routes result in lower wait times and thus lower overall travel time.
- **Transit Mode:** Agencies can decide to serve certain areas of the metropolitan area with bus, subway, commuter rail, streetcar, etc. Bus systems are cheaper and flexible to implement, because of a lack of necessary additional infrastructure. However, buses are slower than rail or subway as they are constrained by road traffic. Subway, rail, and streetcar are more expensive and take more time to build the infrastructure, however, when built, are much faster than buses.
- **Fare System:** There are many different kinds of fare systems including flat fares, distance based fares, and passes for regular riders, elderly, youth, or students. The fare system contributes to the equity of the system.

This thesis will only explore the route frequencies as a lever to influence the metrics above. The location of stops, route designs, transit mode, and fare system as they are today are considered constants for this analysis. Route designs and stop locations are prohibitively expensive to change for rail. While bus network redesigns do happen - WMATA is currently going through a bus redesign⁶⁵ - the process requires a lot of administrative capital that is out of scope for this project. The frequencies of routes are more adjustable, given a sufficient supply of operators and vehicles.

People travel in many different kinds of ways that the agency works to serve as optimally as possible by adjusting the levers above. Travel behavior is determined largely by travel purpose, and people

travel for many different kinds of purposes. The Federal Highway Administration defines these categories as work, shopping, family, and social¹². Work trips include commuting to work as well as travelling for work related business. Family trips include family / personal errands such as dropping off children at school, travelling to care for elderly, or travelling for household organization, maintenance, or administration[§].

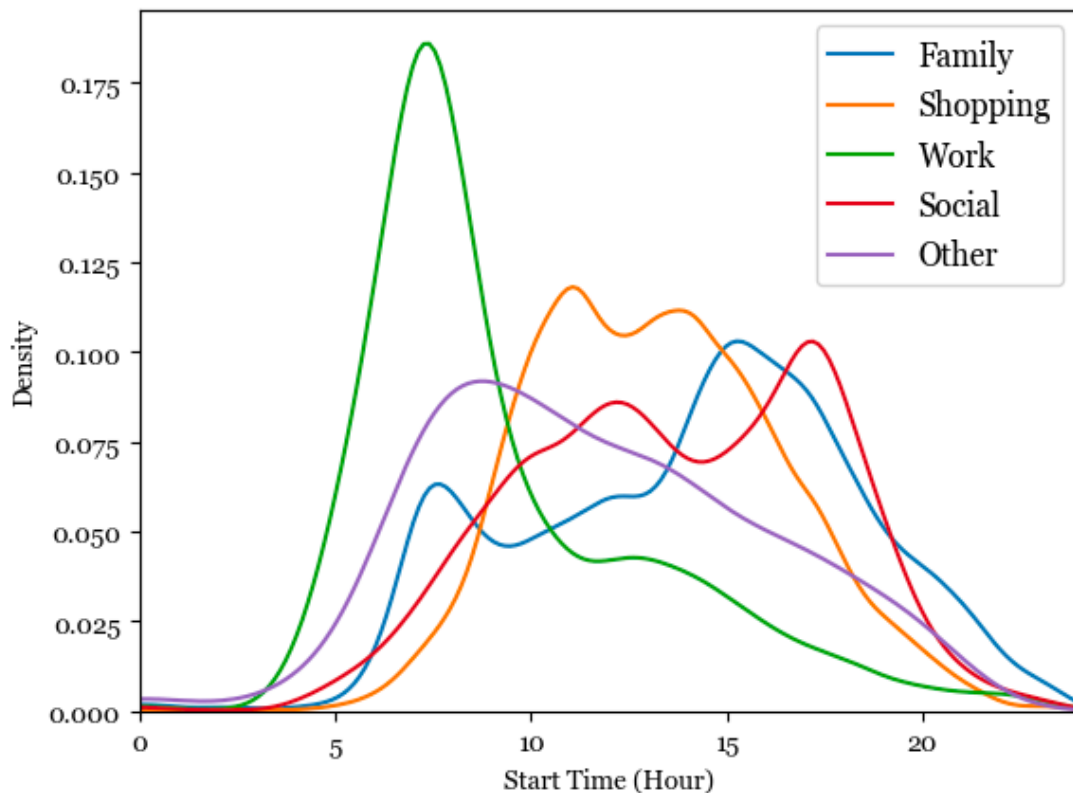


Figure 1.4: Distribution of Trip Start Time by Purpose (NHTS, 2022)³⁴

People travelling for the family, leisure, or shopping disproportionately travel in the middle of the day, in the evenings, and over the weekends (See Figure 1.4)²⁶. Additionally, this travel behav-

[§]While this is the official trip purpose delineation in the U.S. Bureau of Transportation, Prof. Ines Sanchez de Madariaga, the UNESCO Chair for Gender Equality in Technology Policies, argues that these categories do not fairly reflect trips for the household, or "Mobility of Care"²⁷. In this paper, Prof. Sanchez de Madariaga argues that shopping (not leisurely shopping) should be considered as trips for the household.

ior is associated with more intra-city travel (people travelling within the city rather than from or to outside the city)^{26 60}. Researchers and theorists have demonstrated that public transportation prioritizes serving travel patterns that look like those travelling for the purpose of work⁶⁰.

Public transportation agencies should seek to boost ridership and improve the riding experience in their cities. Public transportation is important for urban livability, reducing congestion, increasing safety, boosting the local economy¹⁸, improving health⁶⁰, and many other societal benefits⁶⁰. Public transportation ridership is also key to addressing the carbon emissions reductions goals of many cities⁶². The World Resources Institute claims that improving public transportation by 2030 is a climate imperative. Reducing carbon emissions in cities via good public transportation systems has been an important measure. Drawdown lists improving public transportation as one of the top 100 solutions to climate change⁹. Finding ways to serve the groups of individuals currently choosing to travel using more polluting, private vehicles is an important step in reducing the carbon footprint of cities. If not for all the reasons above, over 75% of Americans would prefer better transportation over driving⁵.

1.3 D.C. AS A CASE STUDY

This thesis focuses on the Washington D.C. metropolitan area. The D.C. area is an apt case study for several reasons. First, D.C. is well studied by the NHTS as well as other transportation related surveys. These surveys provide a helpful theoretical and empirical foundation to understanding public transit trends in the region. Second, according to the survey data, the D.C. region exhibits the national post-pandemic trends illustrated above.

D.C. is also a city that has invested heavily in their infrastructure to support workers. The city is uniquely an "industry town". The central downtown has many office buildings and further out the city becomes more residential. Further, many of the people travelling on public transportation

are workers. In Spring 2023, according to survey data, 65% of Metrorail trips were to or from work, compared to 80% before the pandemic⁶⁴. These worker travel patterns in D.C. are particularly easy to identify because of the peak hour travel.

D.C. has invested in supporting the travel needs of the work-force. The D.C. rail system is designed to bring people in the city during peak hours⁵⁵. Frequency of the rail and bus system increases during peak hours, and decreases during the middle of the day and over the weekend (See Figure 1.5)².

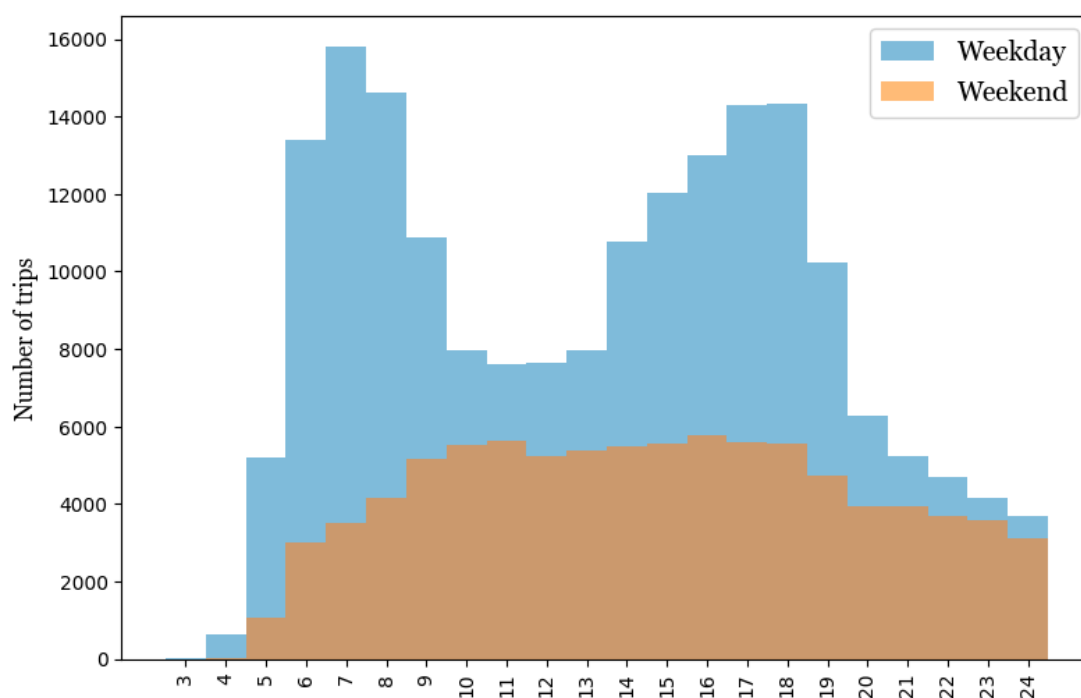


Figure 1.5: GTFS Weekday Service Over the Day, Metrobus and Metrorail¹⁴

D.C. residents are asking for transit that better serves their off-peak needs. Even despite a high personal vehicle travel rate - 81% of people commute with a personal vehicle - we see that over 60% of surveyed citizens in 2022 would ride a better public transport system over driving¹¹. In order to boost ridership, 82% of D.C. residents want to see more convenient time schedules and 72% want

adequate space on service during peak and off-peak times”¹¹. D.C. residents would be open and willing to take public transportation if it fit their mobility needs better.

1.4 OUR CONTRIBUTIONS

This work empirically explores non-commute travel patterns in D.C. using mobile phone data and public transit ridership data. We validate the claims made by surveys on the trends of travel purpose demands in D.C. To the authors’ knowledge, no research studies in D.C. have explored non-work travel behaviors at a larger scale using WMATA individual trip-level data in combination with mobile phone data. This thesis will attempt to identify workers and non-workers, report the differences in travel behavior, and explore the differences in public transportation convenience.

2

Background

DIFFERENT TRAVEL PURPOSES typically exhibit different travel behaviors. It is important for public transportation agencies to plan their systems effectively for each of these travel behaviors in order to serve their communities effectively and equitably. In this section, we will discuss the current public transportation landscape, how it is changing post-pandemic, and how it can be inequitable. Further, we will discuss methods that have been used to explore non-work travel patterns.

2.1 PUBLIC TRANSIT IS DESIGNED FOR WORK

Public transit in the United States has been designed for workers. American cities typically design their public transportation systems *radially*⁶⁰. That is, the transit system is designed to bring people to an identified "downtown". Invisible Women (2019) makes the argument that the *radial* design is optimized for commuters, who typically need to travel into the city for work²⁶. Commuters who need to travel to the city in the morning and out of the city in the evening are well served by this kind of system.

Washington D.C. is not exempt from the worker-centric design. D.C.'s Metrorail (subway) map has a *radial* design (Figure 2.1). According to the city's zoning maps, the office-building dominant downtown is surrounded by lower-density residential areas² (see Figure 2.2). While D.C. and many other American cities also offer bus services, the rail service is faster, resulting in a system that is more convenient for the commuter.



Figure 2.1: D.C. Metrorail Map

There are many other reasons why people travel, i.e. household responsibilities such as getting the groceries or dropping off the kids, socializing, health-related travel, etc. According to the 2017 National Household Travel Survey, 19% of travellers on any given day are travelling for work³³. This suggests that 81% of travellers on any day are people that are travelling for other, non-work purposes. Because American transportation systems have prioritized serving commuters, American cities have underserved the majority of travellers.

In a piece titled "With commuting down, cities must rethink their transportation networks", the Brookings Institution researchers discussed how, post-pandemic, Americans transit networks are not designed for supporting the changes in travel demand³⁷. Many Americans using public transportation need to *trip-chain* to arrive at their final destinations, particularly those travelling for non-work purposes³⁷. *Trip-chaining* means chaining together multiple stages of travel (i.e. needing to transfer to another route sometime during the trip or using some other mode of transit to arrive at the bus stop). This is opposed to direct travel, where one route stops within walking distance of both the rider's origin and destination. One reason is that American cities are not very mixed-use, meaning the cities are compartmentalized by district. In a typical American city, there will be a central business district, residential districts, recreational (more restaurants or other activities), industrial (manufacturing or distribution centers), or others³⁹. The central business district will typically be at the center of the city (see Figure 2.2 for D.C.) and accessible by public transportation. Any other destinations may be distributed around the central business district. There is not always direct service from one part of a neighborhood to another, while there is more likely to be direct service to the central business district. In this way, the design of the transit network is well suited for work travel purposes, but not necessarily other mobility patterns.

We can see this *trip-chaining* phenomenon empirically with survey data. A study using the Nationwide Personal Travel Survey (NPTS), a survey sponsored by the Federal Transit Administration (FTA) of 25k respondents, found that regardless of mode, people travelling from home to home

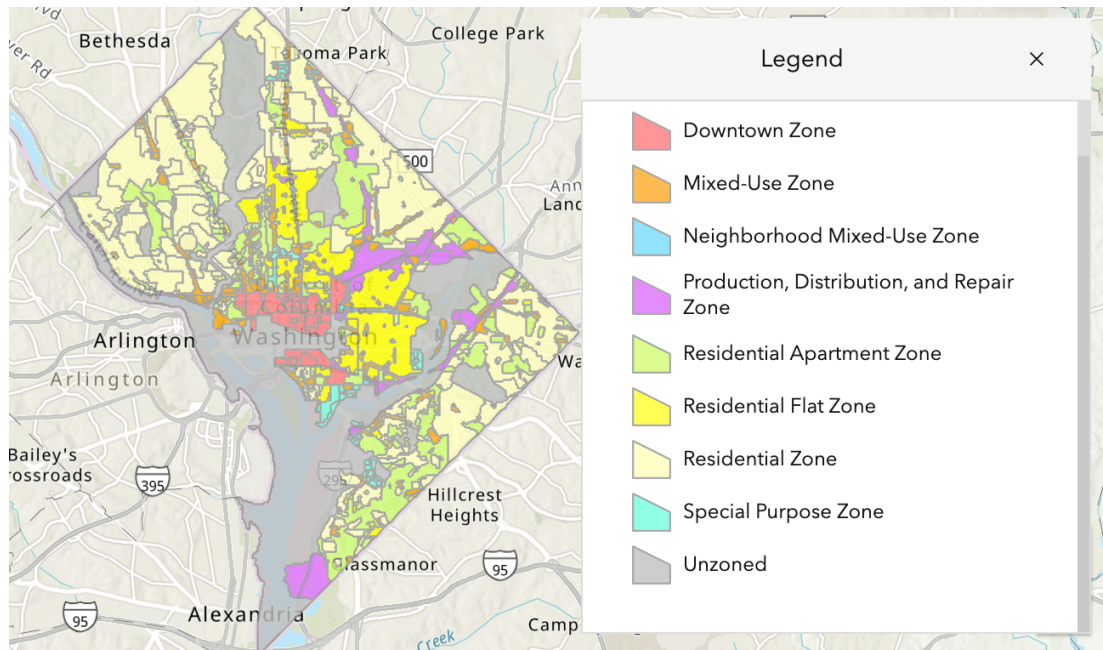


Figure 2.2: Zoning Map of D.C.

(as in leave home to run some errands to come back home) take on average 2 transfers, while people travelling from home to work on average take less than 1 transfer. Women travelling from home to work take an average of .8 transfers while men take an average of .3 transfers⁴⁷, suggesting women may be more likely to stop more to take care of household responsibilities than men. The home-to-work category on the survey may not reflect the multi-purpose trips that women are more likely to perform. Overall, non-work trips are more likely to *trip chain* by over 1 additional transfer. This suggests that more American public transportation riders *trip-chain* to arrive at their final destination if they are travelling for non-work purposes.

Non-work destinations are more dispersed than the concentrated office neighborhoods in many cities. Rail systems with a centralized, *radial* design do not often offer service to other parts of the city outside of the central business district (see Figure 2.1 in D.C.). If a rider needs to travel to a destination outside of the central business district, they would need to travel to the middle of the

city (the office district), and transfer to another line that takes them out to another neighborhood. Jarrett Walker, a transportation expert and author of *Human Transit*, a well cited book that describes the transit priorities in American transit systems, makes the argument that a rail *radial* design is good for workers⁶⁰, but not necessarily other types of travellers. A good example of this is the Boston system. A person who wants to travel from Harvard Square to Back Bay would need to take the Red line into the city, transfer at Park Street, and take the Green Line a few more stops West. A traveller who wants to go to the central business district would only need to ride the Red line one more stop to Downtown Crossing.

Many transit systems try to close the geographic gaps in service using bus systems. Transit agencies in big cities in the US are typically multi-modal. While rail systems are more radial to get people into the central business district, bus systems typically fill in the connectivity gaps between the neighborhoods. Bus systems in American cities can be used to connect neighborhoods in cities, so a traveller doesn't need to go all the way into the center, transfer, and go out along the line that arrives at their destination neighborhood. For example, while Boston has a *radial* rail system, the bus lines connect neighborhoods together without having to go into the central business district¹⁵. Non-work destinations are less concentrated in central districts, and thus, non-commuter travellers are more likely to travel to other neighborhoods in the city. Such bus systems are typically more useful for these kinds of travel patterns because they can travel more directly to their destination rather than travelling into the central district and transferring to go back out.

The consequence of such design is that, given buses are slower than rail lines²⁶, people who rely on using the bus to travel more directly to their destination will be spending more time travelling per mile. In Boston, the average speed of a trip coming from a census tract with a subway stop can be more than 10 minutes a mile faster than census tracts without subway stops (see Figure A.7). So while connectivity in many American cities is relatively comprehensive, the travel time and convenience is not equal across different types of travel patterns²⁷. Using the Boston example above,

riders can travel directly to Back Bay using the Bus 1 line from Harvard Square. However, this Bus 1 line takes more than 20 minutes (without traffic) compared to 10 minutes by car and 15 minutes by bike. Taking the subway takes approximately 40 minutes because the rider needs to travel into central Boston, and transfer to travel south towards Back Bay. The rider would likely choose to take the bus because of the 20 minutes saved, but the rider would be spending more time per mile travelled than someone who would be travelling directly to the central district. Thus, while bus systems may be better placed to suit the needs of non-workers of the transit options available, they can be significantly slower than rail systems, which take workers directly to their destinations faster. The transit modal layout, thus, disproportionately serves the worker.

While the system design and modal choice make it convenient for people to travel for the purpose of work, the route frequencies are also designed to support commute travel patterns. The allocation of system resources over the course of the day has skewed towards planning for *peak hours*⁶⁰. *Peak* hours are typically 8-10am and 4-6pm during weekdays. These hours are characterized by a notable increase in commuters travelling into the city in the morning and travelling out of the city to come back home. In his book "Human Transit", Jarrett Walker makes the claim that public transit has been designed for reducing crowding during the peak hours. This means that route frequencies are higher during times when work trips are happening and lower during times when non-work trips are more likely to be taken place.

Walker also lays out the burdens on the system itself of peak-centric design. Walker claims that peak-centered transit design burdens the system because of the difficulty of finding drivers willing to split their shift between morning and afternoon. In the current transit landscape where many American cities have been facing an operator shortage³¹, squeezing the system further by inconveniencing operators makes addressing this operator shortage even more difficult. Additionally, a higher supply of vehicles is required for a only few hours a day, so public transportation systems have to pay and manage the storage of vehicles without any payments from riders during the middle of the day or

over weekends. Not only is it not optimal for most residents in a community to not be served during non-peak hours, it is also burdensome for the operation itself.

Overall, public transportation in American cities have been designed for work trips. In the following sections, we will dive into the following three problems of a worker-centric design: 1) most people in general travel for the purpose of non-work, so this design is not optimally serving a majority of trips; 2) the demand for non-work travel is increasing, so the work-centric model is also missing a lot of future demand; and 3) marginalized groups (i.e. lower income, racial minorities, and women) tend to depend more on public transportation for non-commute travel purposes.

2.2 SHIFTS TOWARDS GREATER DEMAND FOR NON-WORK TRIPS

The current state of this supply / demand gap in non-work travel is wide in public transportation (as discussed above) and it is growing. Demand for non-work travel has been increasing due to two main factors: 1) fewer people are commuting post-pandemic due to higher rates of working from home¹; 2) more people are moving to denser urban areas and closer to their work and more reliant on public transportation (less able to drive through the city)⁵². In the following section, I will discuss these changes in travel demand.

Nationally, the changes in demand have been driven partly by more people working from home post-pandemic. People are travelling less for the purpose of work. According to the American Community survey, 25% of American workers now work from home, more than three times higher than the 7.2% rate prior to the pandemic². This trend entails a lower demand for work trips. Caros et. al. (2023), demonstrated this by exploring the change in travel purpose post-pandemic using three years of monthly travel surveys²⁴. The surveys revealed that in many American cities, hybrid work arrangements are associated with more non-work trips than in-person work arrangements. The landscape has changed, at least temporarily, potentially permanently, such that a lower proportion

of riders are travelling for the purpose of work.

Another contributing factor to the increase in non-work travel is that more people are moving to the cities, so downtowns are becoming more residential⁵². This leads to two contributing changes in rider demand. As it becomes easier to move around the city using other modes, city residents choose to travel less with the car and more with public transit, walking, micromobility systems (i.e. bikes or scooters), or ride-hailing. It is generally easier to travel around a city without being tied to a personal vehicle. Roads in urban environments are more difficult to navigate and slower than streets in suburban neighborhoods. Additionally, parking can be more cumbersome. Newman and Kenworthy (1999) establish the theory between density and automobile use in their book "Sustainability and Cities: Overcoming Automobile Dependence"⁴⁸. The much-cited book hypothesizes that as people move to the city, automobile dependence decreases. Particularly, the Newman-Kenworthy theory is that per-capita vehicle miles traveled (VMT) decreases in denser urban environments because of the density.

Recent studies have tested this theory using transportation ridership data and have found mixed results, suggesting density is a factor but not the entire story. Ewing et. al. (2017) studied 157 large US metropolitan regions and found that there were more factors contributing to decreasing per-capita VMT in metro regions, not just density³². They found more variation in the model than the original paper. When controlling for per-capita income and average fuel price, an increase in density is a significant contributing factor to the decrease in VMT. As income increases and fuel prices decrease, then VMT increases as well. The picture for what effects car-choice is much more complex than originally claimed in the Newman and Kenworthy theory. Land-use and street connectivity were also found to have much more of an effect on car usage. When more mixed-use and street connectivity design is implemented in cities, people are more likely to travel less with private vehicles and more with other modes of travel, potentially increasing the demand for public transportation services.

People will choose the mode of travel that is most convenient for them. If parking is also hard to find, people will take other modes of transit. As the Brookings Metro Institute argues, the percent of space dedicated to parking in a city is negatively correlated with transportation ridership⁵⁵.

The second notable trend is as density and mixed-use developments increase, non-work travel in the urban environment increases. People tend to leave their dwellings more often than in suburban environments³⁵, potentially related to smaller dwelling sizes. People travel to the grocery store more often, may need to visit a laundromat, and will spend more time socializing outside of their home. The proportion of trips that make up non-work related trips is larger than in suburban areas³⁵. Thus, as city populations grow, the demand for public transportation use changes to more non-work dominant.

2.2.1 GREATER DEMAND FOR NON-WORK TRIPS IN D.C.

We observe these trends in Washington D.C. In Spring 2023, according to survey data, 65% of Metrorail trips were to or from work, compared to 80% before the pandemic⁶⁴. So, according to survey data, more public transportation riders are using the D.C. system for non-work purposes post-pandemic. This could be attributable to two trends in recent years in D.C. that we will explore in more detail in the following paragraphs. First, post-pandemic, there are higher rates of teleworking, so fewer people need to leave their residences to go to work. Second, more people are moving to D.C. proper, increasing the demand for household related trips.

More people in D.C. are teleworking, which according to the theories laid out above, would suggest a lower proportion of ridership demand would be from work-related trips. Approximately 33.8% of people teleworked in 2022, compared to just 6.3% pre-pandemic²¹. A study done by the D.C. Policy Center found that if all office workers went remote, D.C. public transportation would lose approximately 150k commuters, which is 65% of D.C.'s commuters⁴⁵. Thus, the scale of the impact of teleworking on public transportation ridership is large and has contributed to the drop in

work-related ridership⁵⁴.

We also see Washington D.C. growing denser as an urban environment and becoming more mixed use. Partly because of these trends, we see more people are choosing to use public transportation to satisfy their daily mobility needs. First, population in D.C. is indeed increasing. Approximately 117k more people moved to D.C. since 2000 (this is approximately 20% increase)⁸. D.C. ranks 7th among all states in terms of population percentage growth. As laid out above, more people moving to the city translates to lower vehicle miles travelled (VMT) per capita. Second, more people are choosing to not own a car. A plurality of households do not use a car D.C. (35%), where 30% use a car less than daily and 33% use a car daily⁵⁷. This suggests that people do indeed rely on other modes of travel to satisfy their household needs. Only 3% of land in downtown D.C. is dedicated to parking⁵⁴, compared to many other cities in the US ranging up to 40% in downtown Detroit. This suggests that car-travel may be more difficult for D.C. residents because finding parking is cumbersome and expensive. Third, within D.C. there is a push for more mixed-use developments, both from the mayor's office²¹ and from the wider community⁴⁶.

Based on the theories laid out above, I expect these changes in D.C. to contribute to the changing travel-purpose demand curve. I expect that more people will be travelling for non-work purposes within the city on any given day. Preliminary findings have contributed positively to this theory. In Spring 2023, non-work ridership in D.C. reached over 90% of pre-pandemic levels, while work ridership reached only 43% of pre-pandemic levels⁵⁴. The survey results suggest that D.C. non-work ridership is recovering faster from the pandemic ridership than work ridership.

D.C.'s ridership landscape is changing and based on the preliminary evidence above, there seems to be a higher demand for public transportation in general, particularly for non-commute travel patterns.

2.3 TRANSIT DEPENDENCE AND WORKER-CENTRIC DESIGN'S EFFECT ON MARGINALIZED GROUPS

Approximately 28 million Americans are *transit-dependent*¹⁹. These Americans have no way to serve their mobility needs other than by using public transportation. The *transit-dependent* are disproportionately low-income⁴¹ and thus need to use public transportation for a variety of purposes, not just work. Worker-centric public transportation design thus disadvantages many marginalized groups in the US. Public transportation convenience is disproportionately skewed towards the worker, which is more likely to be middle-income and middle-age males. However, most residents in American cities don't fit this demographic group. Studies have identified *transit-marginalized* groups of people, largely people who fall under one or more of the following categories: female, the elderly, those of lower-income, the disabled, and/or a racial minority. There are two contributing factors to being *transit-marginalized*: first, a dependence on public transportation; and second, using public transportation for a travel purpose that the service is not optimally designed for (i.e. household labor).

2.3.1 WOMEN ON PUBLIC TRANSPORTATION

Invisible Women, a 2019 book about the missing data related to female issues, makes the claim that women are part of the *transit-marginalized*²⁶. Women are more likely to be dependent on public transportation and are more likely to use public transportation for non-work related travel.

First, women are less likely to use a private vehicle than men. This is largely attributable to, one, the gender-wage gap because women are less able to purchase a car⁵³, and two, to fewer women having driver's licenses⁵³. For both of these reasons, women are more dependent on public transportation than men. This phenomenon was validated in many cities. An extensive case study with 2000+ survey respondents in the LA metropolitan region ran by LA Metro explored transit dependence

amongst their female riders²⁰. The study found that indeed only 25% of female metro riders had access to a car, compared to 32% of male metro riders. Of female metro riders, 88% take the metro more than 3 times a week. The case study also included participatory workshops with a total of 70 women. Qualitatively, they found that women were "reliant" on transit, spending hours of their day on public transportation to make it to work or appointments.

Second, women are less likely to travel for work and more likely to travel for household purposes (i.e. dropping off the children at school or doing the groceries). Given that most transit systems are not designed optimally for this travel behavior, women disproportionately spend more time on transit and transfer more often, despite travelling shorter distances, than men^{53, 20}.

These trends occur in other cities as well. The International Transport Forum commissioned an aggregation of survey data from 8 different cities across the world in 2018⁴⁹. Using multinomial logistic regression analysis, this study explored the relationship between gender and transport mode choices. Some of the key findings were that women make more non-work trips than men, their travel distances are shorter, and women are more likely to walk or cycle than men. Women are less likely to have direct access to their final destination and thus are more likely to *trip-chain* when compared to men travelling on public transportation²⁶. Sanchez de Madariaga (2017) explored caretakers taking public transportation in Madrid and found that many caretakers *trip-chain* using public transportation to drop off their children or do shopping for the household (i.e. grocery shopping)⁵³. If women have access to a private-vehicle, they are more likely to use the car to go about their travel-needs, because the flexibility is more conducive to this travel-behavior⁵⁶. Thus, women are more dependent on public transportation than men, and women tend to travel for non-work purposes that result in more inconvenient transport experiences.

More generally, *mobility of care* is a useful umbrella category that characterizes a pattern of trip-making related to travelling for the purpose of the household, which is disproportionately female. The first major study conducted on *mobility of care* travel was made through a specifically designed

survey conducted in the metropolitan area of Madrid²⁷. To characterize the nature of *mobility of care* Trips, Sánchez de Madariaga and Zucchini designed and implemented a survey specifically conceived to be able to quantify *mobility of care* trips in the metropolitan area of Madrid. Since then, the *mobility of care* framework has been replicated in a number of cities across the world.

Generally, people using public transit for *mobility of care* exhibit the following behavior:

- *Transit-Dependent*: less likely to use a private vehicle, and more likely to use public transit
- *Off-Peak Travel*: Travel during the middle of the day
- *Trip-Chaining*: More likely to stop while on the journey, either to perform errands or because there is no direct access to the destination.
- *Shorter Distances*: More likely to travel to a closer destination.
- *Accompaniment*: More likely to travel with another person

2.3.2 ELDERLY ON PUBLIC TRANSPORTATION

Elderly individuals are also more reliant on public transportation for non-commute purposes. Those who are elderly are more likely to be retired and are less likely to be able to drive a car. Approximately 15% of individuals in D.C. are above the age of 65. While only 9% of the elderly in D.C. ride public transportation, this is the age group for which this number has increased post-pandemic³⁸. Elderly individuals are more likely to travel for non-work purposes. The travel behavior reflects the non-work travel demands, as elderly individuals are more likely to travel more in the middle of the day and on the weekend³⁶.

2.3.3 DISABLED ON PUBLIC TRANSPORTATION

According to the Travel Patterns of American Adults with Disabilities Survey in 2021, Disabled individuals (between 18 and 65) are more likely to live in a zero-vehicle household than individuals that are non-disabled⁴³. Over 22% of non workers with disabilities, compared with 9.5% non-workers without disabilities, live in zero-vehicle households. Additionally, 12.2% of disabled workers live in zero-vehicle households, compared to 3.9% of workers without disabilities. This suggests that these individuals may be more transit-dependent than non-disabled individuals. Indeed, we see that disabled individuals use a personal vehicle for approximately 9% fewer trips than those that are not disabled. While the rates of using public transportation are low in general, (in this survey transit trips occupied only 2.7% of non-disabled worker trips), the rates of using public transportation are still higher for disabled individuals (at 4.3%).

For non-workers, the dependence on public transportation is higher. While only 3.3% of trips for non-disabled, non-commuters used public transportation in this survey, 5.9% of disabled non-commuters used public transportation to get around. The trip purpose of disabled individuals skews towards non-commute. On average, those that are disabled travel 1 trip less per day than those that are not disabled. However, this difference is coming from disabled individuals travelling less for work trips, social trips, and recreational trips. Disabled individuals travel a similar amount for shopping, errands, and medical / dental trips. This suggests that disabled individuals are more transit-dependent than non-disabled, underscored by the skew towards necessity-driven trips. Further, the travel demand from disabled individuals skews away from work-related trips. This suggests that commuter-centric public transit design does not equitably serve the disabled population.

Overall, women, elderly, and the disabled are more public transit dependent and use public transit more for non-commute related travel behavior. Thus, commuter-centric design unfairly disadvantages women, the elderly, and the disabled.

2.4 METHODS TO EXPLORE NON-WORK TRAVEL BEHAVIOR

2.4.1 SHORTCOMINGS OF SURVEY DATA

Investigating non-work travel patterns presents challenges due to the variety of travel purposes that translate into complicated travel behaviors. While work trips generally exhibit identifiable behavior, described above, non-work travel behavior is defined as a broader category that leads to less predictable behavior.

Many studies on travel patterns rely on survey data to investigate non-work travel patterns. The National Household Travel Survey (NHTS), a survey released by the Federal Highway Administration once at most every 5 years, explores the how, why, and where people move in the U.S.^{33 34}. The data contains the survey respondent location, which allows for exploration of travel behavior in large metropolitan areas. Trip purpose was disaggregated both years into work; school, religion, or daycare; medical or dental; shopping or errands; social or recreational; or other activities. School, religion, and daycare trips were grouped into one category, making care trips difficult to delineate. Further, exploring the changes in non-commute travel behavior post-covid is not reliable with NHTS⁴⁰. The 2022 NHTS had only 7,500 households respond³⁴, compared to the 129,112 households that responded to the previous the NHTS in 2017³³. While NHTS data is commonly used to explore non-commute travel patterns^{51 61 22 23 25 49}, leveraging trip level tap-in/tap-out data on public transportation could provide a more robust solution for studying such behaviors, mitigating concerns associated with small sample sizes and categorization issues.

Overall, while survey data is a useful tool for exploring and explaining some more qualitative aspects of travel behavior, ultimately, it falls short at a more granular level of analysis that allows for detailed and strategic policy making. First, by simplifying the possible responses and reducing the number of categories, the survey structure may introduce bias. Second, the sample sizes are relatively small compared to the sizes available through direct transit fare data. And finally, comparing year to

year findings is logistically difficult because the structure of the survey and survey sample sizes may have changed.

2.4.2 TRANSIT FARE CARD DATA TO INFER TRIP PURPOSE

Transit fare card data has been used to infer trip purpose. Alsger et. al. (2018) used Smart Card data paired with Household Travel Survey data in Brisbane, Australia, and inferred trip purpose using land-use information. There is a high correlation between land-use and trip-purpose¹⁶. The paper identified that points of interest and start times of trips were indeed correlated with trip purpose according to the travel survey data. The methodology observed points of interest within 400 meters of transit stops, the start times of trips, and the activity duration and classified each trip along thresholds along those characteristics. Work trips were inferred correctly 85% of the time and home-purpose trips (trips for the household such as household chores or dropping off the children) were inferred accurately 82% of the time. Home-purpose trips were inferred based on the number of homes within 400 meters of the stop. While this methodology proved to be around 80% accurate for trip origins, this methodology would be difficult to apply when using a broader definition of household purpose trips (i.e. multi-purpose trips that include *mobility of care* but may end up at work).

Inferring specific kinds of non-work travel purposes has had some traction in the literature. A recent paper by Shuman et. al. demonstrated that by using tap-in/tap-out data from D.C., we can identify people travelling for *mobility of care* purposes⁵⁹. The paper uses a methodology that uses *Mobility of Care* points of interest (schools and daycares) and identifies the routes that trip-chained near these points of interest, suggesting that people who transfer near these stations are more likely to be travelling for the purpose of dropping a child off. These findings were supported by demonstrating that women are up to 20-30% more likely than men to perform these kinds of travel patterns. Further, women were only more likely to perform these trips during the weekdays, further

supporting the claim that these trips were *mobility of care* trips.

Transit fare card data has been used to explore travel purposes using different demographic groups. Particularly, transit fare card data has been used to explore the temporal characteristics of the aging population, specifically in Beijing⁵⁸. Since the elderly population (over 60 years old) is less likely to be travelling for the purpose of work, we can extrapolate the temporal behavior of the elderly individuals to non-work travel patterns generally. Shi et. al. (2020) used a subset of over-all smart card data of over 600,000 travellers carrying an Elderly Smart Card ID. They found that elderly were more likely to travel between peak hours on weekdays, where their peaks are usually between 9 and 11am and 2 and 4pm (compared to adult travellers which peaked from 8-9am and 6-7pm). Further, the elderly population was found to travel at similar frequencies as adults. So while there is no obligation to travel for work, elderly individuals still travel at the same frequency. The method of exploring convenience temporally allowed these authors to explore off-peak travellers behavior.

Clustering methods have been used to explore trip purpose based by identifying different demographic groups. Literature has been done on public transportation riders demonstrating the heterogeneity of the customer base. In a 2021 paper, Rafiq and McNally explored travel purpose from 2017 National Household Travel Survey data and used Latent Class Analysis to assign 4 classes of individuals based on activity patterns⁵¹. While two classes were commuters (split by gender), the last three classes were assigned to non-commute based activity patterns. The non-commute classes were defined as 1) employed white millenials that made complex multimodal tours; 2) non-white younger and older adult groups; and 3) members making complex non-work tours with recurrent transit use (dominated by single older women).

Overall, there are several papers that use survey data that establish a necessary theoretical and empirical foundation. However, these papers are based off of potentially biased and limited data sizes that restrict strategists from effectively planning for all of the complexities associated with non-work

travel. While there are a few studies that explore non-work travel patterns on public transportation using transit fare card data, these are limited to exploring specific demographics of individuals.

2.5 OUR SOLUTION

Our work uses WMATA tap-in/tap-out data and mobile phone data to identify and explore non-work travel patterns in the D.C. system in 2019 and in 2022. We identify work travel patterns by observing the peakiness and regularity at which an individual travels. We identify *mobility of care* trips using the methodology proposed by Shuman et. al. (2022)⁵⁹. We measure the change in travel behaviors pre- and post- pandemic to validate the national trends and D.C. survey trends with direct transit fare card data and mobile phone data. We measure the convenience differences of non-work vs. work travel using fare card data.

In the following sections, we will go into more detail about the data used in this analysis. We will then go into more detail about the methodology used.

3

Data Description

We now explore travel behavior within D.C. using three types of sources of data: 1) Transit Data, 2) Mobile Phone Data, and 3) Geographic Data.

3.1 TRANSIT TAP-IN/TAP-OUT DATA

This thesis uses TRACE, a *stage*-level tap-in/tap-out dataset provided by WMATA. A *stage* is a trip leg on a particular WMATA vehicle. This is in contrast to a *journey* which is defined as one or more

stages that start within 2 hours of each other. For example, a rider boarding a bus and then transferring to another bus within 2 hours would be considered a journey with two stages. Both of these stages would be recorded as separate rows in TRACE, recorded with the same *journey key*. People enter onto the WMATA system either by tapping their SmarTrip Card or, if they are travelling on bus, riders can pay using cash. This data contains all methods of fare payment. If the SmarTrip Card was used, then a unique card identifier populates the *card* column in the dataframe.

The dataframe is Origin-Destination-Transfer (ODX), a type of transit data standard created by an inference process developed by MIT Transit Lab³⁹. ODX is created from individual transit fare card transactions (Automatic Fare Collection (AFC)), Automatic Vehicle Location (AVL), and Automatic Passenger Counting (APC)). The AFC data provides the unique card identifier, the tap-in to the system, and the time of entrance into the system. This tap-in could be on any WMATA service, including bus and rail. This thesis uses data from both the bus and rail systems. The AFC data also contains tap-out data for rail stages because riders on the WMATA subway are required to tap-out before they leave the a subway station. The destination time and location is inferred for bus trips using a dynamic programming process. Using the APC data, transfers are inferred for both rail and bus trips. The inferred transfers is how individual stages in TRACE are linked to a journey key.

Each TRACE row contains a few identifying pieces of information: each stage is associated with a journey key, a unique transit card identifier (card id), the number of stages in the associated journey, and the position of the current stage in the stage sequence that makes up the journey. With the same example above, the first bus stage would be entered as a row with a stage sequence of 1, and the second bus stage would be entered as a separate row with a stage sequence of 2. Both would have the same journey key and number of stages in the journey, as well as the same card id. Each TRACE row also contains a few ODX characteristics of the stage: the start place, the end place, the start time, and the end time. Each row also contains the fare instrument, the number of meters travelled, and the total number of seconds in the vehicle. All the rows are described in Table A.1.

The pre-processing section in the Methodology (see Section 4) below describes the process to convert the stages dataframe into journeys.

The TRACE data for 2019 contains 94,214,300 stages, 83,122,145 journeys, and 3,455,634 unique cards. The 2019 data was based on a random sampling of overall tap-in / tap-out data for 2019 because of the size of the dataset. The TRACE data for 2022 contains 143,485,452 stages, 132,776,490 journeys, and 5,540,960 unique cards. The vast majority of journeys have only one stage.

Table 3.1: Summary of Data for 2019 and 2022

Year	Unique Stages	Unique Journeys	Unique Cards
2019	94,214,300	83,122,145	3,455,634
2022	143,485,452	132,776,490	5,540,960

3.2 MOBILE PHONE DATA

The mobile phone data, referred to as location-based services (LBS) data, uses device trajectories and speeds to infer origin, destination, and mode of travel. This data is not just limited to public transportation data. The data includes driving trips, walking trips, and biking trips. The process was developed by Cambridge Systematics and applied to the D.C. area in 2022. Each row represents a representative day of that particular year, quarter, day of the week, trip start hour, start location (multi-block group), end location (multi-block group), and trip purpose. A "representative" day does not mean a specific trip, but rather, of all the trips that happened with the specific set of parameters in that row, they exhibited the characteristics listed on average. For example, a row could be a representative day in 2022, Q1, that was a Saturday and occurred at 9am, starting in census block 1 and ending in census block 2, and for the home-based trip. The convenience characteristics associated with this row would be the average of all trips taken on that day with those characteristics.

Thus, the dataframe is indexed on 7 different columns.

The days of the week are split into 4 different types: Monday - Thursday, Friday, Saturday, and Sunday. The data groups Monday - Thursday together because there are no notable or structural differences between travel patterns on Mondays - Thursdays. Thus, it is reasonable to assume that any day on Monday-Thursday would exhibit similar behavior as any other day on Monday-Thursday.

The data infers 4 types of trip purposes: home-regular, home-other, regular-other, and other-other. The "regular" location is defined as a place that the individual is at for the greatest number of hours (except at a residence) in the 6 month period. The location must be a work-based location or a school-based location.

Each row contains the number of total trips that occurred in D.C. in the subcategory delineated by the indices listed above. The number of trips is separated into mode: auto, rail, bus, walking, or biking. Each row contains a few descriptive characteristics of the average trip in the rows subset, including an average time spent travelling using a car as well as the transit travel time, and the distance travelled in miles. The row contains a few descriptive characteristics of the average traveller in the rows subset. The row contains whether or not the average traveller's inferred home location is in an equity zone. The Majority Low-Income Equity Zones are those that are in the 90th percentile for an Equity index, developed as a function of the number of low-income households, people of color and disabled persons are in the multi-block group. The Low-income zones are 75th - 90th percentile of the Equity index. The Equity Zones are graphed in Figure A.1.

There are 17,670,800 rows in 2019 for a total of 2,334,558,622 trips and 27,682,750 rows in 2022 for a total of 3,278,485,271 trips.

All the rows are described in Table A.2.

3.3 GEOGRAPHIC DATA

The existing WMATA system is defined by a series of routes, each of which travels to some subset of the stops on a particular schedule. Of the 12,703 transit stops in the WMATA system, 12,585 are bus stops and 118 are subway stops. All the stops are mapped in Figure A.2.

The points of interest data were taken from D.C. Open Data: cafes, pharmacies, public schools, private schools, and places of worship⁴. There are 452 cafes, 157 pharmacies, 124 public schools, 54 private schools, and 774 places of worship. The locations are mapped in Figure A.3.

These places of interest were identified as common destinations for non-work purposes. Cafes are popular gathering places where people can socialize, and also reflect mixed-use environments. Pharmacies are more distributed throughout the city. By exploring travel patterns to pharmacies, we can better capture travel patterns whose destinations are outside of the central city. Schools are a good way to capture household travel patterns as parents need to accompany their children to drop them off at schools. Finally, places of worship offer a regular destination that is typically off-peak (typically during the weekends). This allows us to capture some of the predictable travel behavior that is off-peak.

These places of interest allow us to take a more granular analysis and gain insight into the distribution of non-work travel patterns over the entire city.

3.4 DATA LIMITATIONS

This analysis used tap-in/tap-out data provided by WMATA. The original stages data was converted into journeys using the unique card ID. However, the algorithm was unable to connect trips that paid in cash on the bus. Trips paid in cash are more likely to be lower income. Thus, the convenience metrics calculated could be an underestimate, as people who are paying in cash are less likely to be travelling regularly, and thus less likely to exhibit work travel patterns.

Further, destinations were only available for a subset of trips. Since the destinations were inferred for bus trips in the ODX data, this could have led to worse predictions for bus trips than rail trips. Given the large number of data points in this analysis, we do not believe this would have a significant impact on the results.

4

Methodology

4.1 DATA PRE-PROCESSING

The stages table is converted into journeys by identifying *trip-chains*. *Trip-chaining* is when a rider takes multiple stages to get to their destination. Trip chaining is identified by grouping by the unique journey key. Within each unique journey key, the stages are sorted by the stage sequence value. Each journey has a calculated transfer time and overall trip time based on the end and start

times of the respective stages. The journey is considered "central" if the start place of the journey originates from a stop within the central D.C. area, defined as approximately 1 mile radius around the White House, up to the Potomac. An in-vehicle distance was included in TRACE, but a birds-eye distance was calculated using the haversine distance between the origin stop and the destination stop. The average in-vehicle trip distance was approximately 10km and the average birds-eye trip distance was approximately 8km in 2019. This suggests that, on average, 2km are added to every trip compared to a direct route. An optimal path would directly drop a person off at their destination, but, because of the nature of the urban infrastructure, a straight path is not viable. Because of the route design and urban infrastructure, the travel distance is longer than a straight-line optimal path.

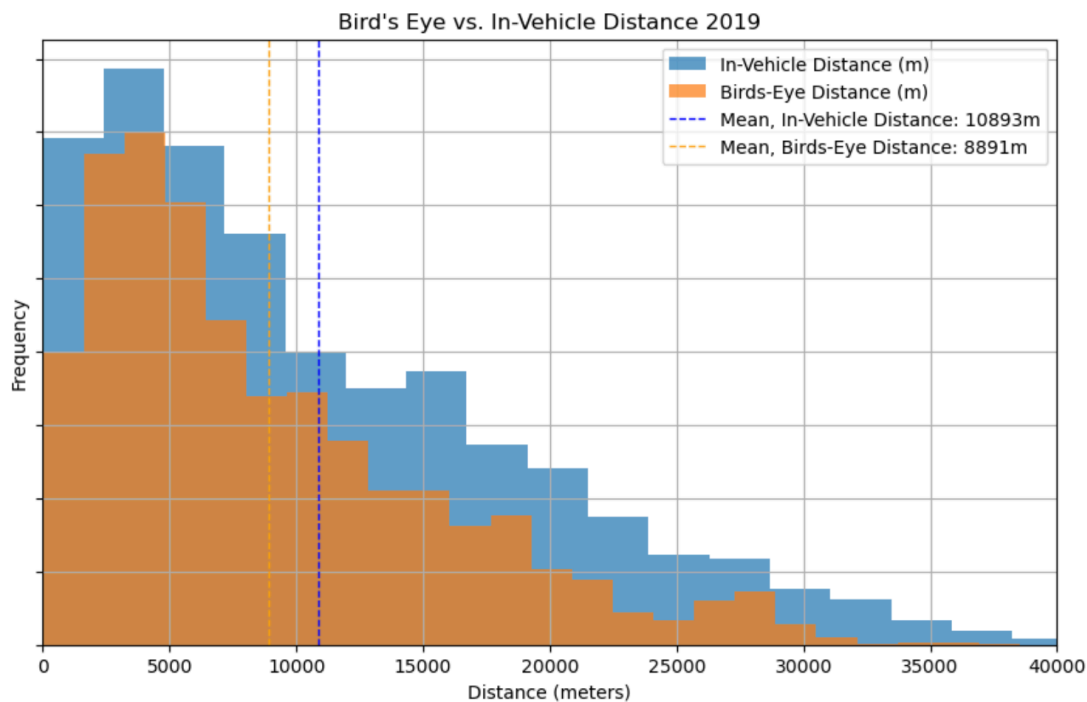


Figure 4.1: Birds-Eye vs. In-Vehicle Distance, 2019

In order to convert the stages table into journeys, the stages table (approximately 130GB) needed to be processed. A threading algorithm was necessary in order to process the stages table without

surpassing the memory threshold. The stages table was split into chunks of size 1 million rows. Each chunk was processed separately and added into an overall journeys file. There could be some journeys that span chunks, which at most would be removing 315 journeys in 2019. This is .0003% of all journeys in 2019, so the effect is minimal. Further, there were 142 chunks in 2022, meaning at most .0001% of journeys could have been interrupted, minimally effecting the data.

Algorithm 1: Process Data in Chunks

Data: stages file, chunk size

Result: Processed data saved to output file

```

1 Function create_journeys ;
   Data: Chunk of stages
   Result: Processed journeys data
2   journeys  $\leftarrow$  convert chunk to journeys ;
3   add journeys to output file
4   Function process_data_in_chunks ;
   Data: Stages
   Result: Processed data saved to Journeys File
5   chunks  $\leftarrow$  pd.read_csv(input_file_name, chunksize=chunk_size) ;
6   futures  $\leftarrow$  [] ;
7   with concurrent.futures.ThreadPoolExecutor() as executor: ;
8     for each chunk in chunks do
9     |   futures.append(executor.submit(process_chunk)) ;
10    end
11    concurrent.futures.wait(futures) ;

```

4.2 INFERRING TRIP-PURPOSE FROM TRACE

Using a similar methodology to Alsger et. al. (2018)¹⁶ and Shuman et. al. (2023)⁵⁹, this thesis flags each journey a Mobility of Care (MoC) trip or not⁵⁹. Roughly, if the journey transfers at a stop near a mobility of care point of interest (a daycare or school), then the journey is classified as MoC.

Specifically, each stop is classified as a *MoC stop* or not. A *MoC stop* must be the closest stop along a route-direction within 400 meters of a daycare or school. A *MoC journey* is defined as a journey that transfers at a *MoC stop*. This methodology is illustrated in the Figure A.4.

A commute trip is inferred based on the following characteristics:

- Travels 90% of the time during peak hours on weekdays
- Is an active rider, travels more than 10 times per month (at least 2 times per week)

This thesis uses the MOC trip methodology to identify non-work trips.

The other characteristics (such as travelling into the city from outside of the city) of commute trips were also observed, but severely limited the pool of values.

4.3 DEFINING CONVENIENCE

Convenience in this thesis is defined as the measure of how quickly and directly a traveller can arrive at their final destination. In order to explore convenience, we observe *travel time*, *wait time*, *trip distance* and *number of transfers*. The trip speed is calculated as the birds-eye distance – haversine distance between the origin and destination – divided by the travel time. The trip speed captures the mode used (bus trips will be slower than rail trips), the time of day (bus trips may be during more traffic congested hours), and the circuitry of the route (routes that take a less direct path and stop more often will be slower).

Transfer times for rail trips are recorded in TRACE as 0 minutes because the rider does not tap in again to transfer rail trips at a station. For this reason, the transfer time calculations below were only between bus trips. Overall, the transfer time for commuters was on average 1 minute vs. 13 minutes for non-commuters (see Figure A.8). This captures the fact that non-commuters were more likely to take buses as well as any convenience difference.

5

Results

In this section, we will describe the findings in relation to the following research questions:

- Has the public transportation demand for non-work-related travel in the D.C. metropolitan area changed between 2019 and 2022?
- Are there disparities in convenience on public transportation between non-work- and work-related travel?

5.1 THE MAJORITY OF OVERALL TRAVEL DEMAND IN D.C. IS FOR NON-WORK TRAVEL

Using mobile phone data, the results confirm that more people are travelling for non-work purposes in D.C. than work using any mode of travel (not just public transportation). This difference is larger post-pandemic.

In 2019, people were leaving the home 43% of the time to go a location other than work or school. In 2022, this statistic increased from 23% to 53.8% (see Table 5.1). The proportion of trips from home to work are approximately the same as the national average, at around 20% of all trips. The percentage of any work related trip has decreased (either from home to a regular location or from a regular location to another destination).

This suggests that when people are leaving the home, they are more likely in 2022 than in 2019 to travel for non-work purposes.

Table 5.1: Mobile Phone Trip Purpose Proportions Pre v. Post Pandemic

Purpose Description	2019	2022
Home-Other	43.2%	53.8%
Home-Regular	19.2%	15.8%
Other-Other	25.0%	23.2%
Regular-Other	12.6%	7.2%

These changes in travel behavior are reflected in the changes of travel demand over the course of the day. People in general are travelling more in the middle of the day and the peaks have flattened (Figure 5.1).

Peak flattening is largely driven by the proportional increase in non-work ridership since 2019 (Figure 5.2). We see a larger number of trips originating from home, but travelling to places other than work or school post-pandemic. Work travel patterns have largely remained the same, other than a slight increase in demand towards the middle of the day and in the afternoon peak (Figure 5.1).

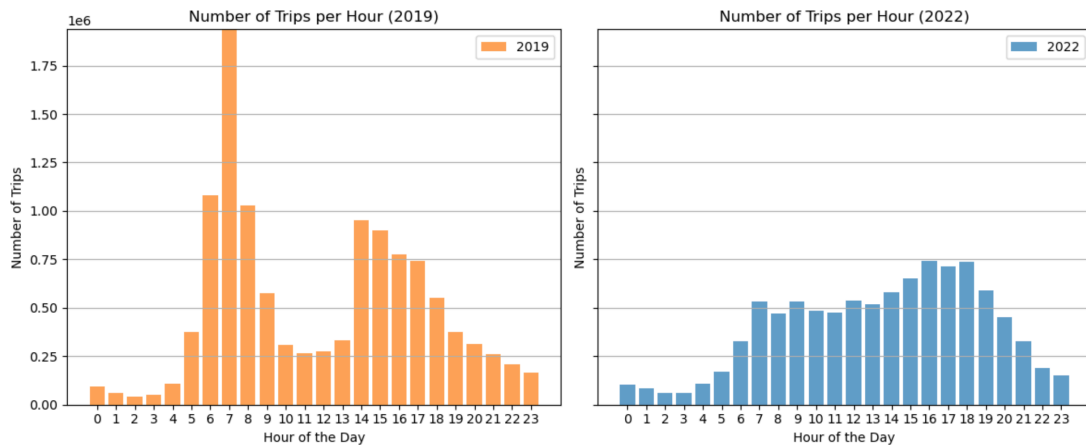


Figure 5.1: Weekday Trip Demand by Time of Day (Mobile Phone)

Non-work travel has less pronounced peaks than work travel, consistently between 2019 and 2022. However, the morning peak for non-work travel is flatter in 2022 than in 2019 (Figure 5.1). In 2022, as soon as people start moving about their day in the morning, the travel demand either remains consistent or grows.

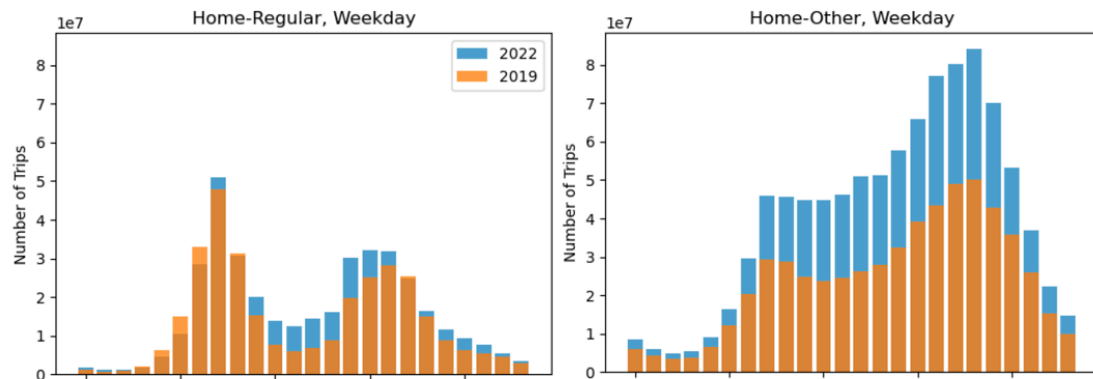


Figure 5.2: Temporal Travel Demand for Work vs. Non-Work Trips (Mobile Phone)

5.2 DISPARITIES IN CONVENIENCE BETWEEN WORK AND NON-WORK TRAVEL PATTERNS

Using tap-in/tap-out data directly from WMATA, we will demonstrate that the D.C. public transit better serves workers through observing the convenience metrics.

5.2.1 IT IS LESS CONVENIENT TO TRAVEL FOR THE PURPOSE OF NON-WORK THAN WORK IN D.C.

This analysis compared the subset of TRACE trips that were identified as work trips and the subset of TRACE trips that were identified as *mobility of care* trips.

Figure 5.3 shows that travel time on average for a *mobility of care* trip is almost double what it is for a work trip. It is not just the case that people travelling for *mobility of care* purposes travel for longer distances. The average *mobility of care* in-vehicle distance is 10.587km and the average commute in-vehicle distance is 10.900km. The travel speeds for non-commute travel patterns are just slower, even when removing transfer time.

Mobility of Care trips by definition will have at least one stop near a daycare or a school. This analysis found that even after accounting for the additional stop, *mobility of care* trips still take slightly more stops to arrive at a destination. So non-work trips are slightly more likely to *trip-chain*, but more rigorous statistical analysis is necessary here (see Section 5.2.2).

Further, non-work trips are more likely to have longer wait times when transfers do happen. This could be attributable to the lower system capacity during the middle of the day, which is when there is higher demand for non-work trips. Lower frequencies can contribute to lower system capacity, meaning time in between vehicles is longer and wait times are longer at each transfer.

We don't see as stark of a difference in travel demand during mid-day using the TRACE data. There is a larger demand during the middle of the day for non-work trips and the work trips have starker peaks both in the morning and afternoon (Figure 5.4a).

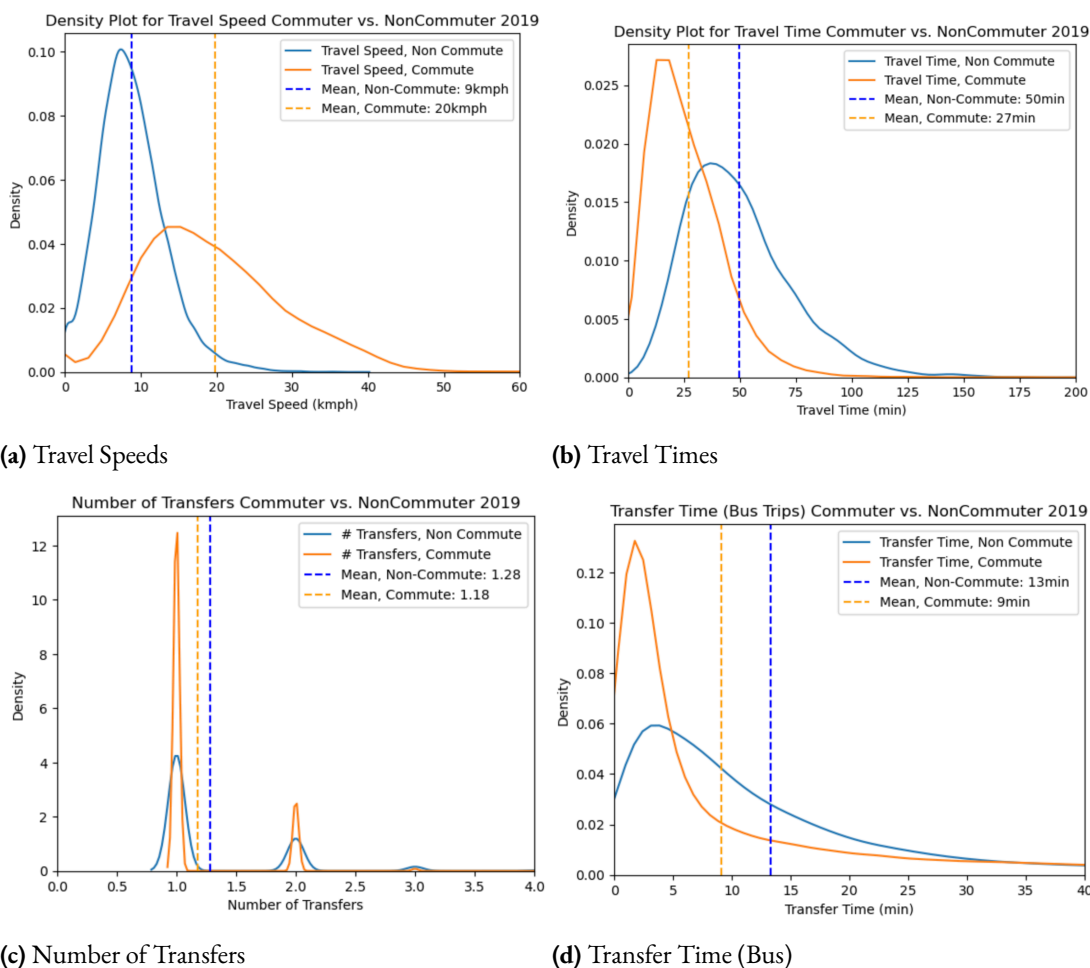


Figure 5.3: TRACE 2019: Convenience Metrics for Commuters vs. Non-Commuters

This suggests that there are lower frequencies around times when people are choosing to travel for non-work purposes, which is leading to longer transfer wait times. Figure 5.4b demonstrates the transit capacity at each hour of the day, observing both rail and bus. We see that during the weekdays, WMATA has a significantly higher capacity during peak hours. This design misses the growing midday travel demand (Figure 5.2), demonstrated by the mobile phone data. While we don't see as stark of a difference in the public transportation data, this may be a reflection of what transit service is offered, and not what transit service is desired. Clearly, residents are travelling more during

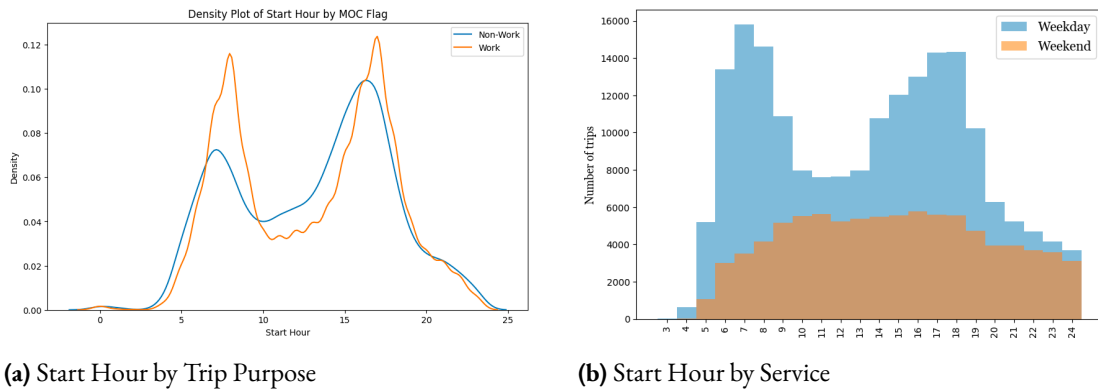


Figure 5.4: Comparing Trip Demand by Purpose and Capacity

the midday, but the transit system is not proportionally serving these travel patterns by prioritizing peak-hour service.

5.2.2 CONVENIENCE STATISTICAL VALIDATION

A Welch's T-Test is a two sample t-test that is used to test whether or not two populations have the same mean, with no assumption of equal variances. A Welch's T-test was conducted to compare the difference of convenience between the worker and non-worker. A separate t-test was run for in-vehicle time, transfers, and travel speed.

The following two assumptions need to be verified in order to apply Welch's T-Test: **independence**, **normality**, and **no extreme outliers**.

1. **Independence:** Each row in the dataset represents a trip. The data could contain multiple rows performed by the same person, travelling the same exact trip. These rows are not independent, as in, the convenience outcomes could be dependent on each other as the same person performs the same trip. Thus, the power of the test may be inflated. A mixed-effects regression below accounts for dependencies between observations by incorporating random effects, such as individual-specific effects (unique card id).

2. **Normality:** An assumption in Welch's T-test is that the sub-populations are Normally distributed around the mean. We can observe the deviation from a normal distribution using a quantile-quantile plot. Both distributions for work and non-work travel times follow a normal distribution generally (Figures 5.5 & 5.6). However, there is some deviation at the tail ends of the travel time. The travel time left-skew is attributable to a few trips that take very long (a few high travel times) and a lower bound. The travel speed left-skew is attributable to a few trips having long distances, but potentially being commuter rail trips, which result in high speed trips. Travel speed is also bounded at 0 kmph.

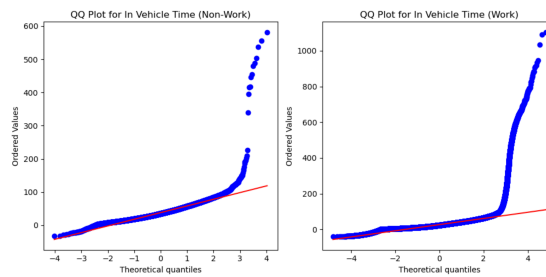


Figure 5.5: QQPlot for In-Vehicle Time for Commuter vs. Non-Commuter

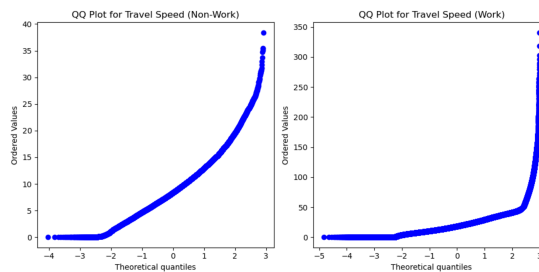


Figure 5.6: QQPlot for Travel Speed for Commuter vs. Non-Commuter

3. **Outliers:** Extreme or influential outliers may influence the results of the test. The travel speed was within the range [0kmph, 38.4kmph]. This suggests there are no outliers on the right tail-end of the distribution. Out of the data, .0042% had trip speeds above 150kmph,

suggesting these outliers. Approximately .01% of trips had in-vehicle times of more than 3 hours. Given the sparsity of the outliers in the dataset, it is unlikely they influenced the results of the test.

The results of the t-test (Table 5.2) indicate a statistically significant difference in the means between work trips and non-work trips. Particularly, a non-work trip is on average 11 minutes longer and is 11kmph slower. The p-values are all below .05. The t-statistics are sufficiently high, however, because of the large number of data points (>10000). The t-value, thus, are inflated and don't necessarily represent the power of the test.

Table 5.2: Welch's T-Test: Convenience Metrics (2019)

Variable	Non-Work	Work	Difference (Non-Work - Work)	T-Stat	P-Value
In-Vehicle Time	37.957	26.877	11.08	77.597	0.0
Transfers	2.299	2.046	0.253	61.816	0.0
Travel Speed	8.82	19.76	-10.94	-359.59	0.0

One way to reduce the inflated power of the t-test is to account for the effects of the unique cards. Using a mixed-effects regression, we can include each unique card as a variable. The results of this test (Table 5.3) demonstrate that even when we account for the dependence assumption the differences in means between non-work and work commute trips is statistically significant. Non-work trips take on average 16 minutes longer in-vehicle than work trips and are approximately 7kmph slower.

Table 5.3: Mixed Linear Model: Convenience Metrics (2019)

	Coef.	Std.Err.	z	P> z	[0.025 0.975]
Trip Speed					
Intercept	6.716	9.206	0.730	0.466	-11.328 24.760
moc_flag[T.1]	-6.579	0.423	-15.563	0.000	-7.407 -5.750
In-Vehicle Time					
Intercept	35.870	36.291	0.988	0.323	-35.260 & 107.000
moc_flag[T.1]	15.778	1.666	9.468	0.000	12.512 & 19.044

6

Discussion

THIS THESIS MAKES THE CLAIM THAT PUBLIC TRANSPORTATION can better serve the needs of their residents if agencies plan better for non-work travel patterns. However, there could be other factors outside of the control of public transportation agencies that influence how easily residents can travel for non-work purposes. I will note two in this discussion: 1) work travel patterns are inherently easier to plan for, and 2) car-centric urban infrastructure (i.e. urban sprawl) may make it

harder for public transportation to conveniently serve travel patterns associated with non-work travel purposes.

First, work travel patterns are inherently more predictable and identifiable, and thus, easier to plan for. Based on the national travel patterns described above, workers are the largest share of riders with both temporally and spatially predictable travel patterns⁶⁰. The distribution of when workers travel is very tight and there is less variation than other travel patterns. Low temporal variation travel patterns are easier for transit agencies to accurately serve. This, however, is changing in post-pandemic America as more people are choosing to work from home and choosing to move to the city, as discussed above. Work travel patterns have changed and have become less associated with the 9-5 Monday through Friday²⁸. This means that transportation agencies will need to accommodate complex travel patterns, not only through the shifting mobility landscape towards non-work travel patterns, but also the growing complexities of work travel patterns.

Second, car-centric urban design (such as urban sprawl) is part of the reason why agencies find it difficult to provide convenient public transportation, but urban design cannot account for the entire reason using public transportation is so inconvenient. In cities designed before the private vehicle, the state of public transportation convenience wasn't always this poor. In older American cities designed before the private vehicle, like D.C., Boston, and New York, a higher percentage of trips were done using public transport than are done now¹⁰. Urban design is sticky, and while the cities have grown, cities like D.C., Boston, and New York still have the same historical street map. Such historical ridership rates demonstrate that in these older cities, urban design should not be an inhibiting factor for more convenient public transportation services.

It should be noted that there are several reasons why people may not choose to take public transportation for non-work purposes. This thesis makes the claim that convenience, defined by travel time, is a factor. There could be other factors that contribute to whether or not someone decides to use public transportation for non-work purposes. First, one of the mentioned goals of a public

transportation agency is to make sure people are comfortable on their system. Perhaps it is simply more uncomfortable to take public transportation for non-work purposes. For example, in order to use transit to pick up groceries, one would need to carry the bags of groceries onto the bus, which is more inconvenient than using a car. Studies have explained an even greater desire for frequent and connected transit when travelling to buy groceries on public transportation²⁹. Additionally, women are more likely to accompany their children on public transportation than in other countries⁷, potentially pointing to a lower sense of assurance with child independent travel on transit. Whether this is for safety or other reasons, there seems to be other factors beyond convenience that contribute to the American reluctance to use public transportation for household purposes.

Second, ride-hailing has recently emerged as a solution to bridge the gap resulting from the shortcomings of public transportation convenience, particularly for non-work-related travel needs. The ride-hailing market has seen tremendous growth in the past several years³. Ride-hailing disproportionately serves people travelling back to the home³⁰ and only 7% of trips taken by ride-hailing are for the purpose of travelling to work. Ride hailing has offered a service for non-work trips that fills in the gaps of public transit. However, this does not alleviate the imperative for public transportation agencies to plan for non-work travel. While it may be more comfortable for people to take a ride-hailed vehicle home than take public transportation, it can be a financial burden. It is important to offer another option for non-work mobility services.

7

Conclusion

PEOPLE TRAVEL FOR MANY DIFFERENT REASONS. People need to travel to go to medical appointments, visit friends and family, pick up the groceries, shop, and go to work. Survey data has demonstrated that travel patterns differ both temporally and spatially based on travel purpose in the US^{20 33 34}. A higher proportion of people are travelling for the purpose of non-work in the US than pre-pandemic. Using mobile phone data from D.C., we see that approximately 10% more trips

are for the purpose of travelling from the home to a non-work destination when compared to pre-pandemic. We demonstrate that the peak-flattening of trip demand for all trips is largely driven by the proportional increase in non-work travel patterns, and not a change in work travel behavior.

Further, marginalized communities including lower-income and racial minorities use public transportation disproportionately for non-work. For both of these reasons, public transportation agencies have an equity-based imperative to plan for non-work travel patterns. Currently, public transportation agencies underserve these travel patterns²⁶. Our analysis using tap-in/tap-out data on public transportation in D.C. demonstrate non-work trips take 85% longer in travel time and 55% slower in travel speed than work trips. We also demonstrated that non-work trips are less direct and need to take on average .1 more transfers than work trips. Bus routes that serve non-work travel patterns on average include a 44% longer wait than work trips. We found these convenience metrics to be statistically significant.

Future work in this area could introduce a more robust mechanism for inferring travel purpose. The Shuman et. al. mechanism used in this thesis does only observe accompaniment patterns. Future work would explore a wider array of non-work travel purposes including medical appointments and socializing. One way to observe macro non-work trends is to establish a gravity model, where the relationship between travel to neighboring grid cells is observed. Such a gravity model would be loosely based off of Gabriel Kriendler's work on measuring economic activity in cities using the gravity model⁴². A first attempt at this using hexagonal units is in Appendix B. While this found no difference pre- and post- pandemic there were some identifiable travel patterns between places with higher concentrations of non-work destinations and travel demand.

Overall, we hope that through this analysis, we can equip agencies with a more robust foundation to better plan for non-work travel patterns. We hope that this will encourage and inform cities across the US to better plan for the mobility needs of people living their lives.



Appendix: Figures

Table A.1: TRACE Data Column Names and Descriptions

Column Name	Description
JNY_KEY	Key identifying a journey
CARD	Unique Card identifier
NUM_STAGES	Number of stages
STAGE_SEQ	Stage sequence within Journey
SUBSYSTEM	MetroRail or MetroBus
START_PLACE	Stop Id for starting place
END_PLACE	Stop Id for Ending place
START_TIME	Start time of stage
END_TIME	End time of stage
VEH_METERS	In-Vehicle meters travelled
VEH_SEC	In-Vehicle Time (seconds)
FARE_INSTRUMENT_ID	Fare instrument ID

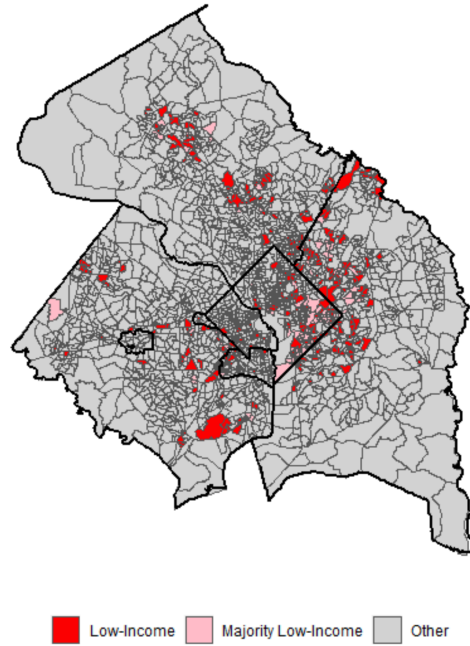


Figure A.1: Equity Zones in D.C.

Table A.2: LBS Data Column Names and Descriptions

Column Name	Description
YEAR	Year
QUARTER	Quarter of the year
WDAY_TYPE	Type of weekday
WDAY_DESC	Description of weekday
WDAY_DESC_DETAIL	Detailed description of weekday
NUM_DAYS	Number of days
ST_HH ₂₄	Start hour
START_MBG	Starting multi-block group
END_MBG	Ending multi-block group
TOTAL_TRIPS	Total trips
AUTO_TRIPS	Auto trips
M_RAILTRIPS	Rail trips
M_BUSTRIPS	Bus trips
M_TRANSITTRIPS	Transit trips
OTHER_TRANSITTRIPS	Other transit trips
WALKTRIPS	Walk trips
BIKETRIPS	Bike trips
AUTO_TRAVTIME	Auto travel time
TRANSIT_TRAVTIME	Transit travel time
TRANSIT_WAITTIME	Transit wait time
DISTANCE_MI	Distance in miles
TRIPLENGTH_AVG_MI	Average trip length in miles
TRIPLENGTH_AVG_DESC	Description of average trip length
PURPOSE	Purpose
PURPOSE_DESC	Description of purpose
EZ_EFC	EZ EFC
EZ_EFC_DESC	Description of EZ EFC
EZ_INCOME	EZ income
EZ_INCOME_DESC	Description of EZ income
VISITOR	Visitor
VISITOR_DESC	Description of visitor

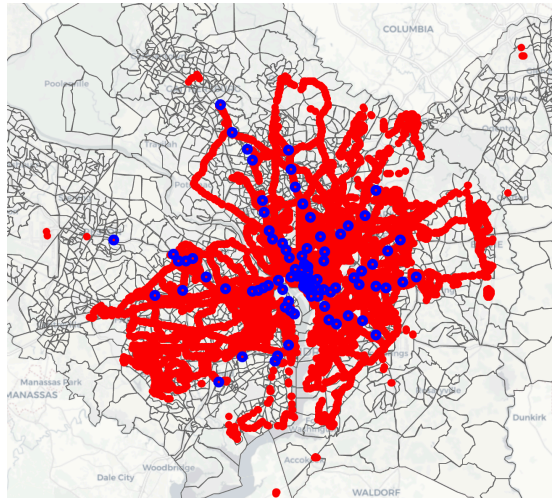


Figure A.2: All stops in WMATA. Red: bus stops; Blue: subway stops

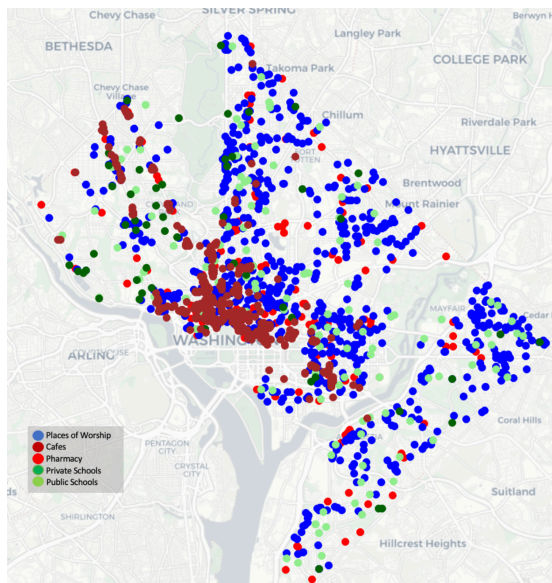


Figure A.3: Points of Interest in D.C.

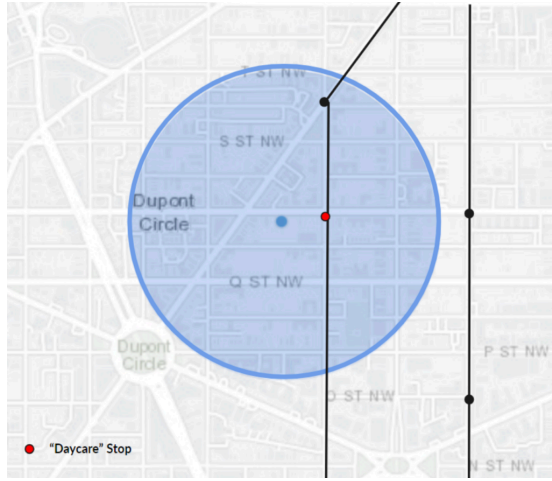


Figure A.4: Mobility of Care Stop Identification Methodology

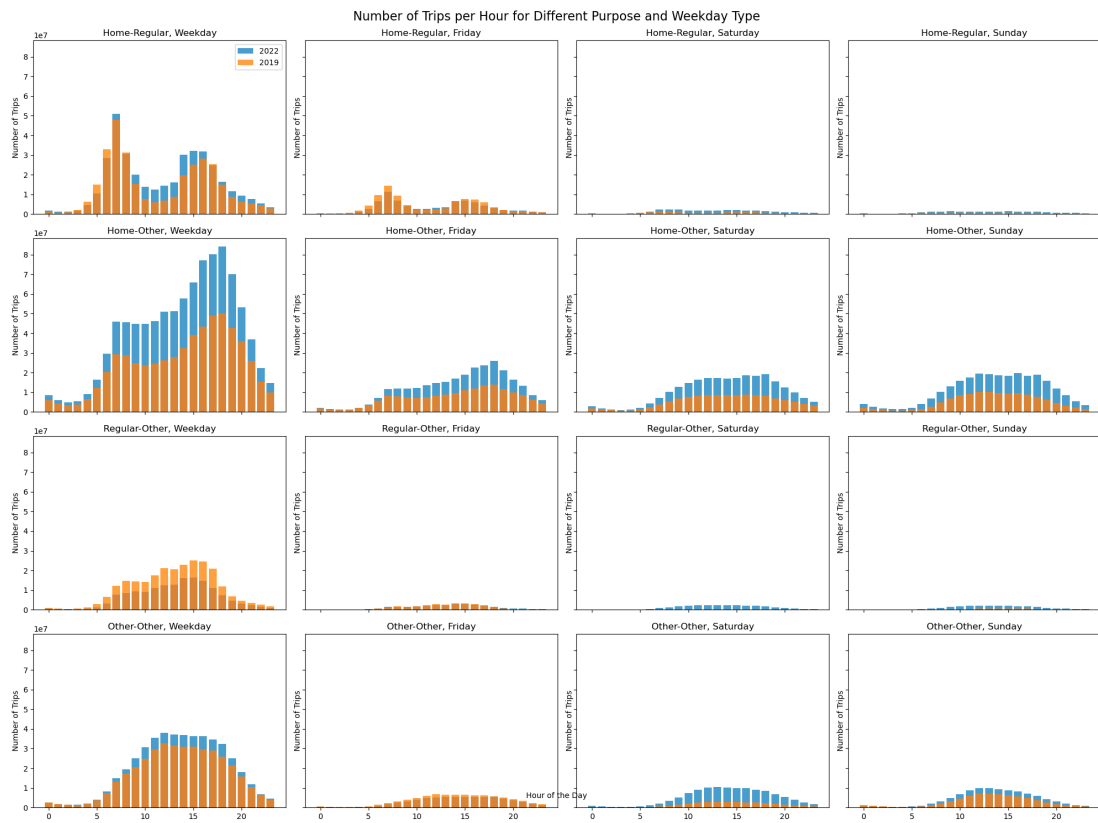


Figure A.5: LBS Trip Purpose and Time of Day, 2019 v 2022

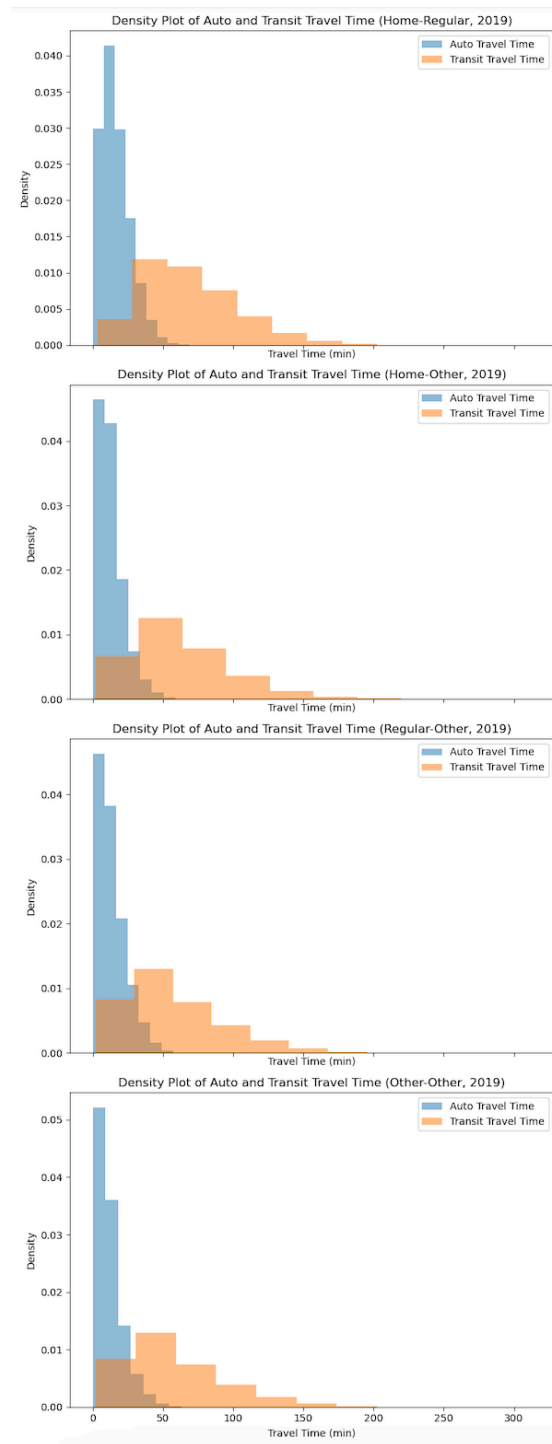


Figure A.6: LBS Travel Time per Mode for Purpose, 2019

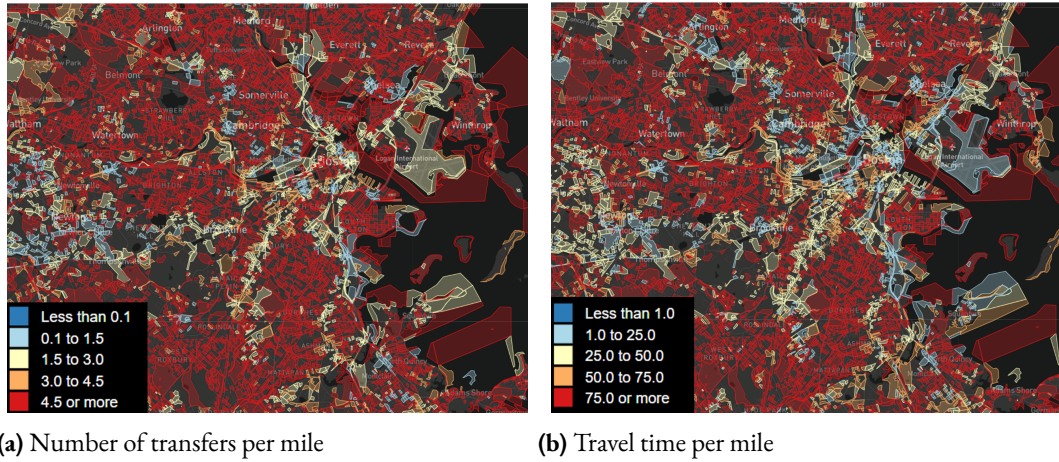


Figure A.7: Census tract level convenience metrics from MBTA data

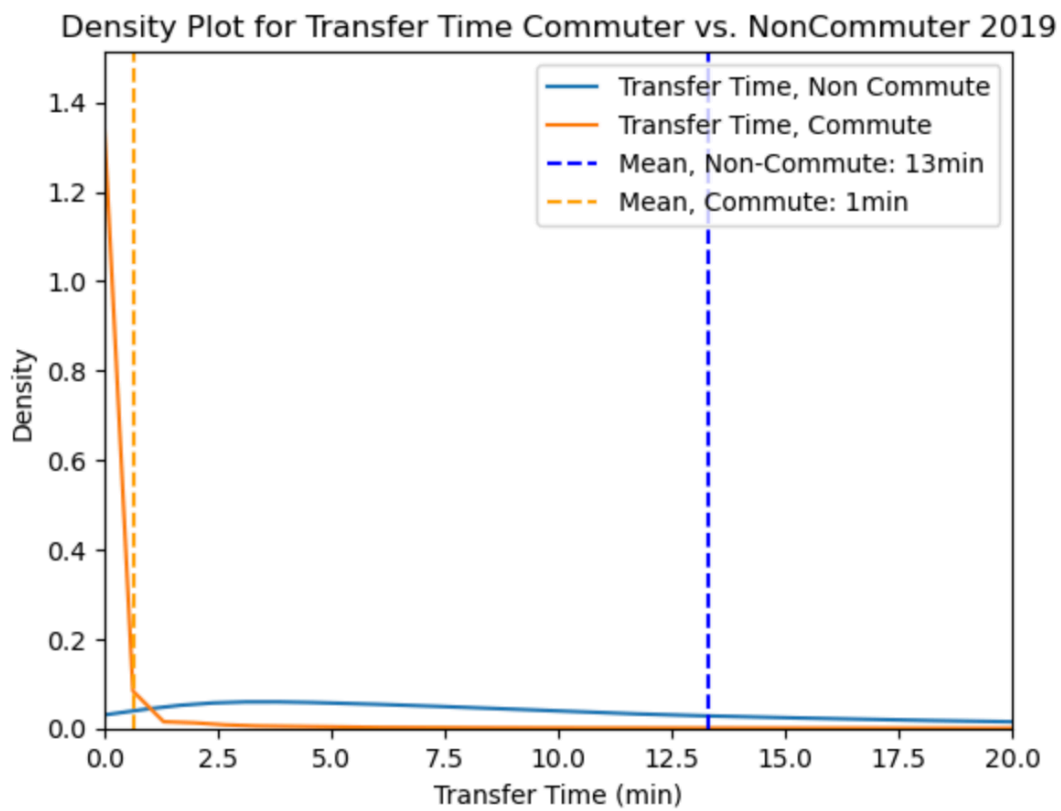


Figure A.8: Transfer Times, 2019 (All Trips)

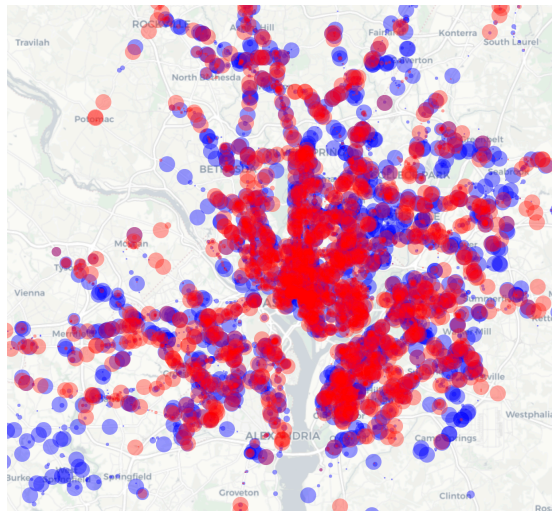


Figure A.9: AM Peak Clustering, Start: blue, End: red

B

Appendix: Results

B.I OBSERVING TRAVEL BEHAVIOR USING NON-WORK PLACES OF INTEREST

B.I.I POINTS OF INTEREST

For this paper, we chose to observe points the following points of interest as potential non-commute destinations. The following points of interest data were taken from D.C. Open Data⁺.

- Cafes
- Public Schools
- Places of Worship
- Pharmacies
- Private Schools

We split up the D.C. Metro into equally sized hexagonal units. Each hexagonal unit will serve as a

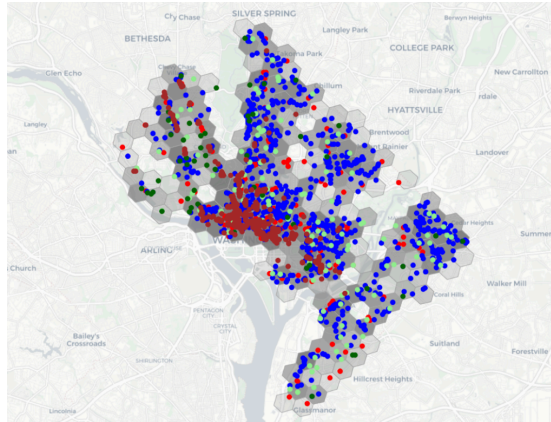


Figure B.1: POIs in Hexagonal Units

group. We will remove the fixed effects for each hexagonal unit.

B.1.2 TRANSIT TRAVEL DEMAND

We obtained the tap-in / tap-out data from WMATA for Quarter 1 of 2019. Each origin stop is associated with a latitude and longitude. We converted this latitude and longitude to the same hexagonal grid mapping above. the travel demand was grouped by origin stop.

B.1.3 OBSERVING TRAVEL DEMAND RELATIONSHIPS

We want to see if there is any relationship between the points of interest and the travel demand to the nearby squares. We grouped the travel demand data with the point of interest data by hexagonal squares and ran the following regression:

$$Y = \beta_i X_i + \alpha_t + \varepsilon$$

Y is the number of people travelling to a location given the number of points of interest X_i for point of interest i , for all points of interest $i \in \{\text{cafes, pharmacies, public schools, private schools, places of worship}\}$. α_t represents the fixed effect for the hexagonal grid cell t , $\forall t \in \{\text{hexagonal grid cells}\}$. β_i represents an increase in the number of travellers if one additional point of interest is added within the neighborhood. ε represents any noise not accounted for in the model.

B.1.4 PRELIMINARY RESULTS

The regression resulted in the following output:

There is a positive relationship associated with all of the places of interest and travel demand. The private schools have the highest associated relationship with travel demand. Particularly, with one additional private school in the grid cell i , there is an associated 46 additional trips originating from grid cell i . Additionally, cafes, which typically generate a lot of foot traffic, are associated with 25 additional trips originating from the grid cell. The results demonstrate there isn't a clear relationship between land-use and ridership in 2019, putting in question the results of the Alsger et. al. (2018) methodology in its applicability to D.C. ¹⁶.

In 2022, we also don't see a significant relationship.

Table B.1: OLS Regression Results

Dep. Variable	count					
R-squared	0.095					
Model	OLS					
Adj. R-squared	0.031					
Method	Least Squares					
F-statistic	1.483					
Date	Fri, 10 Nov 2023					
Prob (F-statistic)	5.55e-05					
Time	13:24:21					
Log-Likelihood	-23698.					
No. Observations	2733					
AIC	4.776e+04					
Df Residuals	2551					
BIC	4.884e+04					
Df Model	181					
Covariance Type	nonrobust					
	coef	std err	<i>t</i>	<i>P</i> > <i>t</i>	[0.025	0.975]
const	48.4131	279.362	0.173	0.862	-499.386	596.213
pharmacy	2.2308	72.214	0.031	0.975	-139.373	143.834
worship	0.0354	14.639	0.002	0.998	-28.669	28.740
publicschools	3.9010	183.691	0.021	0.983	-356.297	364.099
privateschools	46.7201	135.208	0.346	0.730	-218.408	311.849
cafes	25.5878	16.081	1.591	0.112	-5.945	57.121
hex_id_882aa84093ffff	-36.0658	508.287	-0.071	0.943	-1032.763	960.632
hex_id_882aa84095ffff	-33.0735	589.325	-0.056	0.955	-1188.678	1122.530
hex_id_882aa84097ffff	-92.2113	511.832	-0.180	0.857	-1095.859	911.437
hex_id_882aa84407ffff	-31.5960	550.272	-0.057	0.954	-1110.622	1047.430
hex_id_882aa84413ffff	-31.0909	632.504	-0.049	0.961	-1271.365	1209.183

Table B.2: OLS Regression Results

Dep. Variable	coef	std err	t	P> t	[0.025	0.975]
const	42.8885	247.265	0.173	0.862	-441.974	527.751
pharmacy	-1.2837	63.929	-0.020	0.984	-126.642	124.075
worship	0.0274	12.961	0.002	0.998	-25.387	25.442
publicschools	3.9236	162.589	0.024	0.981	-314.897	322.744
privateschools	37.5527	119.672	0.314	0.754	-197.112	272.218
cafes	23.3576	14.234	1.641	0.101	-4.553	51.268
hex_id_882aa84093ffff	-35.9710	449.875	-0.080	0.936	-918.132	846.190
hex_id_882aa84095ffff	-28.6659	521.600	-0.055	0.956	-1051.473	994.141
hex_id_882aa84097ffff	-78.7517	453.013	-0.174	0.862	-967.065	809.562
hex_id_882aa84407ffff	-26.0488	487.034	-0.053	0.957	-981.074	928.977
hex_id_882aa84413ffff	-27.5420	559.816	-0.049	0.961	-1125.286	1070.202

References

- [1] American Community Survey (ACS). Section: Government.
- [2] D.C. Zoning Maps.
- [3] Global Ride Hailing Services Market Size & Share Report, 2030.
- [4] Open Data DC.
- [5] Smart mobility: enhancing public transport | Hitachi Rail | Hitachi Rail.
- [6] WMATA | Ridership Data Portal.
- [7] (2010). *Women's Issues in Transportation: Summary of the 4th International Conference. Technical papers*. Transportation Research Board. Google-Books-ID: 1tuqWyoo6SAC.
- [8] (2020a). Total Population Trends | edscape.
- [9] (2020b). *Transportation @ProjectDrawdown*.
- [10] (2021). Transit Use, Automobility, and Urban Form: Comparative Trends and Patterns | Making Transit Work: Insight from Western Europe, Canada, and the United States – Special Report 257 | The National Academies Press.
- [11] (2023). Study Reveals Shocking Number of People Who Prefer Public Transport Over Driving.
- [12] (2024a). FHWA - Chapter VII. Trip Purpose.
- [13] (2024b). *The High Cost of Transportation in the United States*. Technical report, Institute for Transportation & Development Policy. Section: Car Culture.
- [14] (2024c). Schedules and Maps | WMATA.
- [15] (2024d). Subway | Schedules & Maps | MBTA.
- [16] Alsger, A., Tavassoli, A., Mesbah, M., Ferreira, L., & Hickman, M. (2018). Public transport trip purpose inference using smart card fare data. *Transportation Research Part C: Emerging Technologies*, 87, 123–137.

- [17] Anderson, M. (2016). Who relies on public transit in the U.S. | Pew Research Center.
- [18] APTA (2020). *Economic Impact of Public Transportation Investment*. Technical report, APTA.
- [19] APTA (2023). *PUBLIC TRANSPORTATION FACT BOOK*. Technical report.
- [20] Authority, L. A. C. M. T. (2019). *Understanding How Women Travel*. Technical report, LA Metro.
- [21] Bahrapour, T. (2023). Remote work thrived again in 2022, new data show, with D.C. a top hub. *Washington Post*.
- [22] Blumenberg, E. & Pierce, G. (2012). Automobile Ownership and Travel by the Poor: Evidence from the 2009 National Household Travel Survey. *Transportation Research Record*, 2320(1), 28–36. Publisher: SAGE Publications Inc.
- [23] Blumenberg, E. & Pierce, G. (2014). Multimodal travel and the poor: Evidence from the 2009 National Household Travel Survey. *Transportation Letters*, 6, 36–45.
- [24] Caros, N., Guo, X., Zheng, Y., & Zhao, J. (2023). *The impacts of remote work on travel: insights from nearly three years of monthly surveys*.
- [25] Collia, D. V., Sharp, J., & Giesbrecht, L. (2003). The 2001 National Household Travel Survey: A look into the travel patterns of older Americans. *Journal of Safety Research*, 34(4), 461–470.
- [26] Criado Perez, C. (2019). Invisible Women. In *Invisible Women* (pp. Chapter 1, Can Snow Clearing by Sexist?).
- [27] de Madariaga, I. S. & Zucchini, E. (2019). Measuring Mobilities of Care, a Challenge for Transport Agendas. In C. L. Scholten & T. Joelsson (Eds.), *Integrating Gender into Transport Planning* (pp. 145–173). Cham: Springer International Publishing.
- [28] DePillis, L., Goldberg, E., & Koeze, E. (2023). Most Americans still have to commute every day. Here’s how that experience has changed. *The New York Times*.
- [29] Dharmadhikari, N. & Lee, E. (2015). Average opportunity-based accessibility of public transit systems to grocery stores in small urban areas. *Cogent Engineering*, 2(1), 1068968.
- [30] Dias, F. F., Laveri, P. S., Kim, T., Bhat, C. R., & Pendyala, R. M. (2019). Fusing Multiple Sources of Data to Understand Ride-Hailing Use. *Transportation Research Record*, 2673(6), 214–224. Publisher: SAGE Publications Inc.
- [31] Dickens, M. (2023). *On the Horizon: Planning for Post-Pandemic Travel*. Technical report, American Public Transportation Association.

- [32] Ewing, R., Hamidi, S., Tian, G., Proffitt, D., Tonin, S., & Fregolent, L. (2017). Testing Newman and Kenworthy's Theory of Density and Automobile Dependence. *Journal of Planning Education and Research*, 38, 0739456X1668876.
- [33] FHA (2017). *National Household Travel Survey 2017*. Technical report.
- [34] FHA (2022). *National Household Travel Survey 2022*. Technical report.
- [35] Frank, L. D. & Pivo, G. (1994). Impacts of Mixed Use and Density on Utilization of Three Modes of Travel: Single-Occupant Vehicle, Transit, and Walking. *TRANSPORTATION RESEARCH RECORD*.
- [36] Gebresselassie, M., Alavi, S., & Hong, A. (2024). How and Where Did Older People Travel Before and After COVID? Insights from Washington, DC's Smart Card Data. *Findings*. Publisher: Findings Press.
- [37] George, C. & Tomer, A. (2023). With commuting down, cities must rethink their transportation networks.
- [38] George, J. & Guskin, E. (2023). D.C. region views Metro positively despite recent struggles, poll shows. *Washington Post*.
- [39] Gordon, J. B., Koutsopoulos, H. N., & Wilson, N. H. M. (2018). Estimation of population origin–interchange–destination flows on multimodal transit networks. *Transportation Research Part C: Emerging Technologies*, 90, 350–365.
- [40] Joe Cortright (2024). Alleged Decline In Transportation Trips Is The Result Of Bad Data Analysis — Streetsblog USA.
- [41] Kea Wilson (2021). U.S. Has More Car-Free Areas Than You Think — Streetsblog USA.
- [42] Kreindler, G. E. & Miyauchi, Y. (2023). Measuring Commuting and Economic Activity inside Cities with Cell Phone Records. *The Review of Economics and Statistics*, 105(4), 899–909. _eprint: https://direct.mit.edu/rest/article-pdf/105/4/899/2142605/rest_a_01085.pdf.
- [43] Lawrence, S. (2022). *Travel Patterns of American Adults with Disabilities* | *Bureau of Transportation Statistics*. Technical report, Bureau of Transportation Statistics.
- [44] Marshall, A. (2022). Public Transit Systems Refocus on Their Core Riders. *Wired*. Section: tags.
- [45] McConnell & Sayin, Y. (2022). Remote work and the future of D.C. (Part 1): How is remote work changing the geography of work in the District of Columbia? - D.C. Policy Center. Section: Economy.

- [46] McConnell, B. (2021). Is mixed-use the future of downtown D.C.? - D.C. Policy Center. Section: Economy.
- [47] McGuckin, N. & Murakami, E. (1999). Examining Trip-Chaining Behavior: A Comparison of Travel by Me.
- [48] Newman, P. & Kenworthy, J. (1999). *Sustainability and Cities: Overcoming Automobile Dependence*. Island Press. Google-Books-ID: pjatbiavDZYC.
- [49] Ng, W.-S. & Acker, A. (2018). *Understanding Urban Travel Behaviour by Gender for Efficient and Equitable Transport Policies* | *International Transport Forum Discussion Papers* | *OECD iLibrary*. Technical report, International Transport Forum, Paris, France.
- [50] Nuria Fernandez (2022). 2022 American Public Transportation Association (APTA) Annual Conference | FTA.
- [51] Rafiq, R. & McNally, M. G. (2021). Heterogeneity in Activity-travel Patterns of Public Transit Users: An Application of Latent Class Analysis. *Transportation Research Part A: Policy and Practice*, 152, 1–18.
- [52] Ritchie, H. & Roser, M. (2023). Urbanization. *Our World in Data*.
- [53] Roberts, M. (2016). *Fair Shared Cities: The Impact of Gender Planning in Europe*. Routledge. Google-Books-ID: NfgGDAAAQBAJ.
- [54] Rowlands, D. (2023). Transit in the Washington region has a future, if we plan for it.
- [55] Rowlands, D. & Loh, T. H. (2023). Ensuring the intertwined post-pandemic recoveries of downtowns and transit systems.
- [56] Scheiner, J. (2020). Changes in travel mode use over the life course with partner interactions in couple households. *Transportation Research Part A: Policy and Practice*, 132, 791–807.
- [57] Sementelli, N. (2022). How much do people in the District really drive?
- [58] Shi, Z., Pun-Cheng, L. S. C., Liu, X., Lai, J., Tong, C., Zhang, A., Zhang, M., & Shi, W. (2020). Analysis of the Temporal Characteristics of the Elderly Traveling by Bus Using Smart Card Data. *ISPRS International Journal of Geo-Information*, 9(12), 751. Number: 12 Publisher: Multidisciplinary Digital Publishing Institute.
- [59] Shuman, D., Abdelhalim, A., Stewart, A. F., Campbell, K. B., Patel, M., de Madariaga, I. S., & Zhao, J. (2022). Inferring Mobility of Care Travel Behavior From Transit Origin-Destination Data. Publisher: arXiv Version Number: 3.
- [60] Walker, J. (2011). *Human Transit: How Clearer Thinking about Public Transit Can Enrich Our Communities and Our Lives*.

- [61] Wang, R. (2015). The stops made by commuters: evidence from the 2009 US National Household Travel Survey. *Journal of Transport Geography*, 47, 109–118.
- [62] Welle, B., Kustar, A., Tun, T. H., & Albuquerque, C. (2023). Post-pandemic, Public Transport Needs to Get Back on Track to Meet Global Climate Goals.
- [63] WMATA (2018). *WMATA FY2019 Proposed Budget*. Technical report.
- [64] WMATA (2023). *Fleet of the Future Design Review, Safety & Operations Committee*. Technical report, WMATA.
- [65] WMATA (2023). WMATA Better Bus.