AN ATLANTA-BASED ANALYSIS ON THE FEASIBILITY OF EMPLOYEE COMMUTE OPTIONS PROGRAMS AND SWITCHING FROM DRIVING ALONE TO ALTERNATIVE COMMUTE MODES

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AN ATLANTA-BASED ANALYSIS ON THE FEASIBILITY OF EMPLOYEE COMMUTE OPTIONS PROGRAMS AND SWITCHING FROM DRIVING ALONE TO ALTERNATIVE COMMUTE MODES

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<td>TDM</td>
<td>Transportation Demand Management</td>
</tr>
<tr>
<td>SOV</td>
<td>Single-Occupant Vehicle</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information Systems</td>
</tr>
<tr>
<td>GTFS</td>
<td>General Transit Feed Specification</td>
</tr>
<tr>
<td>API</td>
<td>Application Programming Interface</td>
</tr>
<tr>
<td>COVID-19</td>
<td>Coronavirus Disease 2019 (COVID-19)</td>
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<tr>
<td>ACS</td>
<td>American Community Survey</td>
</tr>
<tr>
<td>NHTS</td>
<td>National Household Travel Survey</td>
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<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
</tr>
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<td>TOPICS</td>
<td>Traffic Operations Program to Increase Capacity and Safety</td>
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<tr>
<td>DOT</td>
<td>Department of Transportation</td>
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<tr>
<td>MPO</td>
<td>Metropolitan Planning Organization</td>
</tr>
<tr>
<td>FHWA</td>
<td>Federal Highway Administration</td>
</tr>
<tr>
<td>UMTA</td>
<td>Urban Mass Transportation Administration</td>
</tr>
<tr>
<td>TIP</td>
<td>Transportation Improvement Plan</td>
</tr>
<tr>
<td>TSM</td>
<td>Transportation System Management</td>
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<tr>
<td>EPA</td>
<td>Environmental Protection Agency</td>
</tr>
<tr>
<td>NAAQS</td>
<td>National Ambient Air Quality Standards</td>
</tr>
<tr>
<td>TCM</td>
<td>Transportation Control Measures</td>
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<tr>
<td>CAAS</td>
<td>Clean Air Act Amendments</td>
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<tr>
<td>SIP</td>
<td>State Implementation Plans</td>
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<tr>
<td>CEU</td>
<td>College Equivalent Unit</td>
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<td>ISTEA</td>
<td>Intermodal Surface Transportation Efficiency Act</td>
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<tr>
<td>FTA</td>
<td>Federal Transit Administration</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>CMAQ</td>
<td>Congestion Mitigation and Air Quality</td>
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<tr>
<td>TEA-21</td>
<td>Transportation Equity Act for the 21st Century</td>
</tr>
<tr>
<td>MAP-21</td>
<td>Moving Ahead for Progress in the 21st Century Act</td>
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<tr>
<td>FAST</td>
<td>Fixing America's Surface Transportation Act</td>
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<tr>
<td>VMT</td>
<td>Vehicle Miles Travelled</td>
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<tr>
<td>EBTR</td>
<td>Employer-Based Trip Reduction</td>
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<td>TRO</td>
<td>Trip Reduction Ordinances</td>
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<td>AVR</td>
<td>Average Vehicle Ridership</td>
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<td>ECO</td>
<td>Employee Commute Options</td>
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<tr>
<td>TRP</td>
<td>Travel Reduction Program</td>
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<tr>
<td>SOVMT</td>
<td>Single-Occupancy Vehicle Miles Traveled</td>
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<td>BWC</td>
<td>Best Workplaces for Commuters</td>
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<td>SHRM</td>
<td>Society for Human Resource Management</td>
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<td>TCRP</td>
<td>Transit Cooperative Research Program</td>
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<td>TCQSM</td>
<td>Transit Capacity and Quality of Service Manual</td>
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<tr>
<td>HOV</td>
<td>High-Occupancy Vehicle</td>
</tr>
<tr>
<td>VTR</td>
<td>Vehicle Trip Reduction</td>
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<tr>
<td>MSA</td>
<td>Metropolitan Statistical Area</td>
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<td>ARC</td>
<td>Atlanta Regional Commission</td>
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<tr>
<td>MARTA</td>
<td>Metropolitan Atlanta Rapid Transit Authority</td>
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<tr>
<td>GCT</td>
<td>Gwinnett County Transit</td>
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<tr>
<td>ATL</td>
<td>Atlanta-Region Transit Link Authority</td>
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<td>TMA</td>
<td>Transportation Management Associations</td>
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<tr>
<td>ADA</td>
<td>Americans With Disabilities Act</td>
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<tr>
<td>TNC</td>
<td>Transportation Network Companies</td>
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SUMMARY

Transportation demand management (TDM) as a concept aims to reduce commuters’ reliance on gasoline-powered single-occupant vehicles (i.e. traditional cars) for travel. At the workplace level, employer-based TDM has assumed the form of commute options programs where employers utilize financial incentives and workplace perks to entice employees to switch from driving to alternative commute modes. However, employer-based TDM initiatives may fall short of their lofty objectives for various reasons, including the effects of local geography and the availability and accessibility of alternative commute modes to begin with. One limitation in current employer-based TDM and research literature is the question of how to realistically assess the potential customer market and segment commuters according to the most suitable alternatives.

This thesis, and the incorporated Atlanta, GA employer case study, aims to offer a practical methodology that can be used to evaluate the competitiveness of available alternative commute modes and identify the modes with the most potential for commuters to switch to. This research considers factors such as travel time, service availability, number of transfers, distance between transfers, and first/last-mile distances for each mode choice. This approach can be easily replicated for other employers and cities beyond this specific case study, provided that there is data available to perform the analysis. This case study adds valuable insight to the employer-based TDM discussion by demonstrating how a feasibility analysis for a potential customer market (i.e. employees at a specific workplace) may be performed.
CHAPTER 1: INTRODUCTION

Employee commute options programs – also known as employer-based transportation demand management (TDM) programs – are rooted in the philosophy of TDM and trip reduction. There is a long history of TDM policies and efforts undertaken by both the public and private sectors in the United States, although the name and shape of such efforts has varied over time. However, a common goal has persisted throughout, which is to reduce employees’ reliance on gasoline-powered single-occupant vehicles (i.e. traditional cars) for traveling to and from work.

To this end, employee commute options programs today often focus on incentivizing employees to switch from driving alone to using an alternative commute mode. These alternative modes range from public transit (e.g. rail or bus), ridesharing (e.g. carpooling or vanpooling), “active commuting” (e.g. biking or walking), to even alternative work hour arrangements (e.g. telecommuting) where possible (Griffin 2020). Carrot-and-stick approaches are often used to motivate employees to make the switch – such as rewarding alternative mode users with financial incentives and/or workplace perks, or even imposing charges for driving and parking.

In addition, the benefits of adopting alternative modes are often extolled to the employee audience to make these options appear more attractive to potential users. Commonly cited benefits of alternatives to driving alone include reducing travel times and commute-related stress, saving commute costs, improving commuter satisfaction, creating a more sustainable environment, and so on. Employer-based TDM proponents and enthusiasts tend to emphasize, perhaps overtly so, that employee commute options programs can and will help create lasting behavioral changes. All parties involved in this enterprise – namely employers, employees, and society at large – are assumed to reap rewards from adopting TDM approaches and goals.
However, in reality every employee commutes options program is different in both its execution and outcomes. Success rates may vary greatly from employer to employer, or even from one workplace location to another. Why is this the case? Truthfully speaking, there may be unique local conditions, constraints, and factors which affect the ability of employees to adopt and maintain the use of alternative commute modes. Because of this, any employer that intends to pursue TDM initiatives for the long term should be aware of potential barriers and challenges. For example, employers should consider the availability of alternative modes – which vary from city to city – and whether these options are reliable and accessible for employees from where they live. As much as possible, feasibility and evaluation studies should be conducted from time to time to assess if the TDM strategies used are on track and suit the needs of the employee population.

This thesis is a case study of a specific employer in Metro Atlanta, GA and its workplace TDM initiatives. The research assesses the feasibility of switching from driving alone to using alternative modes – primarily transit, active commuting, or a mix of both – for employees. It aims to examine what alternative modes are available to employees and if these modes are competitive with driving alone, with travel times being a key point of comparison. Practical constraints such as distances to transit stops, number of transfers, and overall travel distances are also considered. The tools used for this research include: (i) Geographic Information Systems (GIS) software for mapping employees’ home addresses, (ii) publicly available trip planner and transit data tools (i.e. Google Distance Matrix API and OpenTripPlanner 1.5) which are equipped with General Transit Feed Specification (GTFS) formatted transit schedules for planning and analyzing travel options, and (iii) scripts in the Python and R programming languages for making Application Programming Interface (API) requests to obtain trip recommendations, retrieve travel information, and process and analyze data. In addition, available employee data is evaluated to assess workplace mode share.
versus the potential customer market for alternative commuting. Based on the findings, several recommendations are made for the employer’s consideration. This thesis includes notes on how the recent COVID-19 pandemic has posed challenges for employee commute options programs – especially in terms of affecting enthusiasm for shared modes of travel, such as transit or ridesharing – and the potential future consequences of these developments.

This work offers value to the field of employer-based TDM by providing a reference point for TDM practitioners who are looking to evaluate the feasibility, market potential, effectiveness and sustainability of their own workplace initiatives. It is hoped that the results of this research will be of benefit to other TDM practitioners and advocates.
CHAPTER 2: BACKGROUND

2.1 Car Commuting and Its Impacts

The daily commute to and from work may seem like a necessary evil and an inevitable fact of the average person’s working life. However, the consequences of this daily travel go beyond the immediate question of whether a commuter arrives at their destination on time and safely. Behaviors develop into habits; over time and on a greater scale, these collective habits become trends that leave magnified impacts on public health, society and the environment. The story of the average American commuter, which more often than not involves driving alone between home and work, is one such phenomenon whose impacts cannot be underestimated.

For more than a century now, the experience of American commuters has been extremely car-centric. The rise of the gasoline-powered automobile vis-à-vis other transportation modes in the United States began in the early twentieth century. This was not an inevitable phenomenon, but one that was enabled by a web of interrelated technical, economic, political and socio-cultural factors (Sovacool 2009, 417). For one, the mass production and cheap prices of automobiles, coupled with rising incomes, made car ownership a real possibility for ordinary Americans as early as the 1910s and 1920s. The development of transportation infrastructure increasingly emphasized road and highway construction, with the latter becoming the second largest item of government expenditure in the 1920s (Joo 2007, 45-46). The easy availability of cars promised individuality, privacy, freedom, mobility, independence, convenience, meritocracy and universalism to Americans – especially for rural citizens not served by public or fixed-line transportation. In contrast, competing modes such as horses, streetcars, and electric vehicles gradually fell out of favor as they were deemed slow, limited, and old-fashioned by consumers (Sovacool 2009, 425).
Crucially, the rise of the automobile made it possible to develop land and housing beyond the confines of the city, leading to the emergence of automobile suburbs in the 1920s. Compared to the transit suburbs of the past, automobile suburbs were significantly different as they were dispersed far beyond the areas served by public transit. Residents of these new suburbs could work in other suburbs without having to go to city centers, as long as they had access to a car. Consequently, by 1941 there were at least two thousand communities across the US with populations of 2,500-50,000 residents who were completely dependent on cars for travel (Jackson 1985, 181-186). Boosted by government policies and cheap mortgages, the suburbanization of housing in the US exploded in the post-war era, alongside soaring volumes of car sales and car registrations. At the same time, public transit funds effectively dried up, with 70% of post-war government spending for transportation going towards highways as opposed to 1% for urban transit. This combination of factors resulted in increasing dependency on cars for daily travel, and by 1960 two-thirds of Americans were driving to work each day (Joo 2007, 45-46).

Ultimately, the growth of suburbanization and urban sprawl over the last century led to the large metropolitan areas of today which are both low in population density and interconnected by roads more so than transit. Because of this, residents of US cities generally continue to rely on cars for daily travel due to the lack of connectivity between residential areas and trip destinations, and the inadequacy of transit, walkway and bike infrastructure in these cities (Resnik 2010, 1853). To date, the United States is the most motorized country in the world; US car ownership levels in 2017 were at over 800 cars per 1,000 people, surpassing other countries by a large margin. As of 2018, only 8.5% of American households had no vehicle, 32.5% had one vehicle, 37.1% had two vehicles, and the remaining 21.9% of households had three or more vehicles (Davis and Boundy 2020, 227). If only households with workers are considered, the share of households with no
vehicle is halved to around 4% (U.S. Department of Transportation 2020, 3-7). In line with these trends, driving alone remains the predominant mode for commuting to work (accounting for 76.4% of workers) as shown by the 2018 American Community Survey (ACS). The 2018 ACS also revealed that other modes such as carpooling (9.1%), transit (5.0%), walking (2.7%), bicycle (0.6%), other means (1.3%), and working at home (4.9%) lag far behind, which is consistent with prior years and even decades. According to US Census data, the share of workers who drive alone has in fact increased by 12 percentage points since 1980 (from 64.4% to 76.4%), equivalent to 52.9 million workers more who drive alone in 2018 versus 1980 (Davis and Boundy 2020, 9-22).

Concerns about the impact of car commuting en masse have been raised by many studies, papers, policy briefs and news headlines. Passenger cars have been identified as major contributors to fuel consumption, greenhouse gases, and air pollution in metropolitan areas. A typical passenger vehicle has a fuel economy of 22 miles per gallon and emits about 404 grams of carbon dioxide per mile or 8,887 grams per gallon (U.S. Environmental Protection Agency 2018). With the average commute trip via private vehicle being 11 miles as of 2017 (McGuckin and Fucci 2018, 79), this translates to around 260 gallons of fuel used and 2.3 metric tons of carbon dioxide released through commuting activities alone by the average car commuter in a year (U.S. Environmental Protection Agency 2021). Carbon dioxide, which is a major greenhouse gas, traps heat in the atmosphere and contributes to climate change (U.S. Environmental Protection Agency 2017). In terms of public health impacts, rising temperatures due to climate change increase the risk of heat-related illnesses and deaths. Climate change also increases ground-level ozone and particulate matter in some locations, which raises the risk of respiratory stress for residents there (U.S. Global Change Research Program, n.d.). Passenger cars themselves are sources of air pollution in the form of ozone production, particulate matter and air toxics generated from the vehicles’ fuel combustion
engines. These pollutants have been linked to respiratory illnesses, cardiovascular problems, cancer, and other health disorders (U.S. Environmental Protection Agency 2016).

Traffic congestion due to car commuting is also a major cause for concern. As observed by the 2017 National Household Travel Survey (NHTS), vehicle commutes are predominantly tied to weekday morning and evening hours, occurring between 6 a.m. and 9 a.m. and between 4 p.m. and 7 p.m. respectively. Since commuting activity is “regular in frequency, time of departure, and destination”, car commuting en masse culminates in the ‘peak rush-hour’ phenomenon and contributes to local traffic congestion. From the early 1980s when national congestion indices were first applied up till 2017, road congestion has steadily trended upwards in urban areas of all sizes, with a 15% increase from 2010 to 2017 (U.S. Department of Transportation 2018, 2-18; U.S. Department of Transportation 2020, 2-8). Respondents to the 2017 NHTS reported spending more time commuting due to congestion (accounting for 75% of respondents) versus other intervening factors such as construction, bad weather, and accidents (U.S. Department of Transportation 2018, 3-4 and 3-14). 2017 estimates suggest that on average, commuters must allow 34 minutes for important freeway trips that would take 20 minutes in light traffic (or nearly 70% more travel time), so that they can arrive on time while compensating for the unpredictability of congestion. In 2017, the cost of congestion to urban Americans was estimated at an extra 8.8 billion hours and an extra 3.3 billion gallons of fuel, resulting in a total congestion cost of $179 billion. For the average commuter, this equates to an additional 54 hours spent in congestion and 21 gallons of fuel, and $1,080 spent in wasted time and fuel (Schrank, Eisele, and Lomax 2019).

Additionally, from a public health perspective, studies have suggested that car commuting is associated with elevated rates of sedentary behavior, physical inactivity, disability, air pollution, stress, and lower quality of life, especially where long commutes are concerned. This is in contrast
to other modes such as walking, taking public transit or biking to work, which are associated with positive health outcomes (Henning-Smith, Kozhimannil, and Evenso 2018; Morabia et al 2010; Humphreys, Goodman, and Ogilvie 2013).

2.2 Transportation Demand Management

In response to the challenges brought about by car commuting en masse, Transportation Demand Management (TDM) policies and initiatives have been attempted over the decades in order to reduce car dependency in travel. TDM today generally constitutes the “application of infrastructure, information, financial, vehicle, technology and support strategies and policies to influence travel behavior in one of three ways… [which are to] reduce vehicle trips and vehicle miles of travel by encouraging the use of shared vehicle and non-vehicle travel options; redistribute where and when travel occurs to shift travel from peak travel locations and periods; or eliminate the need to travel at all” (Winters et al 2020, 1). In short, TDM approaches to influencing travel behavior involve affecting how, when, and where people travel (Victoria Transport Policy Institute 2014). Crucially, the philosophy of TDM represents a paradigm shift away from traditional supply-side congestion mitigation techniques, which have historically involved widening or adding roads. Opponents of the latter approach tend to argue that the relief to traffic congestion effected by road expansion is temporary. As per the Law of Peak-Hour Traffic Congestion coined by economist Anthony Downs, peak-hour traffic congestion eventually rises to meet maximum capacity as potential travelers notice fluid traffic on previously clogged roads and move to refill them (Downs 1962). In other words, adding more road space only encourages drivers to continue more of the same behavior, i.e. car use, albeit on larger and larger scales until there is no more room or funds for expansion. In contrast, TDM aims to disrupt these behavioral patterns and nudge road users towards commuting alternatives.
The following sections explore these topics: (i) how TDM has been conceptualized and implemented by both the public and private sector (as government policy and workplace initiatives respectively), (ii) what employer-based TDM looks like today, and last but not least (iii) the factors that affect the effectiveness of employer-based TDM initiatives.

2.3 Transportation Demand Management in the Public Sector

2.3.1 Early Efforts and Drivers of TDM Policy

In US government policy, the idea of managing transportation demand is certainly not new although the justifications for and strategies employed in its pursuit have varied by time and place. Nonetheless, Meyer (1999, 579) argues that “the evolution of TDM as an important component of transportation policy is difficult to benchmark.” This is because TDM actions have often not carried the TDM label, despite having been tried for many years in many different contexts.

For example, prior to any federal policy on TDM actions, many communities especially in California had already experimented with various congestion management actions to lessen travel demand at certain sites. Wachs, Chesney, and Hwang (2020)’s report titled *A Century of Fighting Traffic Congestion in Los Angeles, 1920-2020* chronicles a history of such attempts; even in the earlier half of the century, Los Angeles tried promoting public transit as an alternative to driving, regulating drivers via partial parking bans, diverting drivers away from traffic congestion via radio broadcasts, and so on. These early attempts were spurred by city officials’ fears that because of traffic congestion, “economic growth might cease and visitors might not return to the city recalling an awful experience” (Wachs, Chesney, and Hwang 2020, 6). Therefore, at the local level, desires to manage traffic were mostly underpinned by anxieties about economic competition and survival.

As for TDM’s roots at the federal level, these can be traced to as early as the 1940s albeit in response to wartime pressures. As the United States entered World War II in 1942, it faced a
severe rubber shortage due to Japanese seizure of rubber plantations in the Pacific, amounting to 97 percent of US supply. The US also faced shortages of gasoline and spare parts at various parts of the war. This prompted the federal government to regulate the public's use of valuable resources such as motor fuel and tires, by rationing rubber and gasoline and lowering speed limits to 35 mph to reduce gasoline consumption per mile. The federal government also undertook a massive propaganda campaign to implore Americans to alter their driving habits and comply with wartime regulations (Frohardt-Lane 2012, 337). Thanks to resource rationing, voluntary carpooling via “car sharing clubs” and carpool matching was widely promoted among many public and private organizations. Participating entities included federal government agencies, workplaces, churches, neighborhood groups, and so on (Chan and Sheehan 2012, 97). The US Department of War in 1942 also issued instructions to companies involved in war production efforts to conduct commuting surveys of employees, submit plans for carpooling programs, and encourage public transit use among employees (Ribner 1981, 62). Despite these efforts, there is little to no information today on the actual level or overall scale of ridesharing that took place during World War II (MIT “Real-Time” Rideshare Research Project 2009), and the effects were arguably short-lived. Frohardt-Lane (2012) argues that rather than interrupting Americans’ attachment to the automobile, wartime government messaging instead solidified driving as a fundamental part of American culture. For instance, propaganda for car-sharing programs encouraged Americans to identify driving with freedom, and to view car-sharing in wartime as the best way to “help insure a lot more freedom for [themselves] later on” (Frohardt-Lane 2012, 148). Limiting one’s travel via driving alone was framed as a temporary inconvenience to be rewarded later (with more driving!), and not as a permanent shift in behavior.
Post-World War II, transportation policies and decision-making during the 1950s and early 1960s mostly “emphasized major highway construction and long-range master planning” (Ribner 1981, 64). However, as automobile traffic and demands on transportation systems increased and their effects grew worse with time, policies were developed to address different concerns and crises that arose. Retroactively, these initiatives can be categorized as TDM initiatives, although they were not explicitly named or framed as such at the time (Greenwald 2019, 7). In fact, it was not until the 1970s that managing travel demand emerged as a visible concept in federal and local urban transportation policies. To some extent, this idea came about in response to declining funds for the supply of new transportation infrastructure; in the wake of the Federal Aid Highway Act (1956), federal transportation infrastructure funding peaked at 1964 at just over 0.5% of national gross domestic product (GDP) but then declined by 40% over the next 10 years (Davis 2016). That said, several critical issues emerged which ultimately drove policymakers and transportation planners to consider how existing urban transportation systems could be better managed to satisfy travel demands, without having to build new roads (Meyer 1999, 579-585). In no particular order, these critical issues involved: (1) traffic management, (2) energy conservation, and (3) air quality.

2.3.1.1 Traffic Management

Traditionally, the term ‘traffic management’ has referred to activities undertaken to control the movement of traffic by altering the designated use of road space. However, Meyer (1999, 580) notes that over time, goals for traffic management initiatives have ranged from increasing traffic efficiency and capacity to providing alternatives for large-scale infrastructure investments.

At the federal level, one such initial attempt involved a 1957 US Bureau of Public Roads study on coordinating different types of traffic management methods on Wisconsin Avenue in the District of Columbia to improve its overall operating efficiency (Carter 1962). This study then led
to a federal-level demonstration program in 1966 – later made permanent in 1968 – called the Traffic Operations Program to Increase Capacity and Safety (TOPICS) to maximize the efficiency of the existing street system (Lacy 1972). Importantly, TOPICS approval of plan submissions was contingent on the coordination of the said plan with the development and improvement of public transit services. This approval condition effectively signaled that the idea of traffic management was evolving beyond a roads-only focus (Meyer 1999, 580).

At the same time, transportation officials openly discussed and considered ways in which traffic management strategies could be used to enhance public transit – and vice versa – that did not involve large capital expenditures, especially for rail transit systems (Meyer 1978). The US Department of Transportation (DOT)’s 1971 Report to Congress was an example of this, being the first US DOT policy document to identify broadly defined traffic management techniques such as express bus services, reserved bus lanes, auto restricted zones and ridesharing as potential solutions for transportation woes (US Department of Transportation 1971). Subsequently, the concept of traffic management became established in US DOT’s highway and transit programs, motivated by the desire to enhance roadway efficiency in light of reduced federal expenditures (Meyer 1999, 582).

These developments led to further federal regulations regarding transportation planning at the metropolitan level, specifically in relation to Metropolitan Planning Organizations (MPOs) which had been formed in the 1960s for urban areas with more than 50,000 residents. According to joint planning regulations issued in 1975 by the Federal Highway Administration (FHWA) and the Urban Mass Transportation Administration (UMTA), each MPO was tasked with creating an urban transportation plan and transportation improvement plan (TIP) which had to include transportation system management (TSM) elements (Association of Metropolitan Planning
FHWA and UMTA’s 1975 regulations identified four groups of TSM actions, namely (1) actions to ensure the efficient use of existing road space, (2) actions to reduce vehicle use in congested areas, (3) actions to improve transit service, and (4) actions to increase transit management efficiency. This initial list of TSM actions thus “represented the coming together of the different traffic management thrusts that had been occurring in the two US DOT modal agencies”; specific examples of said actions included reduced vehicle use and peak-period travel, traffic operations improvements, preferential treatment for high-occupancy vehicles, provisions for pedestrians and bicycles, parking management, transit improvements, and so on (Meyer 1999, 582). A 1978 US DOT-commissioned report further clarified TSM actions as influencing supply or demand, via the categories of (1) reducing demand (e.g., ridesharing), (2) enhancing supply (e.g., area-wide traffic signal timing), (3) degrading supply while reducing demand (e.g., take-a-lane high occupancy vehicle (HOV) facility), or (4) enhancing supply while reducing demand (e.g., add-a-lane HOV facility) (Wagner and Gilbert 1978).

Despite these efforts, Ferguson (1999) argues that TSM did not gain widespread acceptance in the transportation planning community in the 1970s. The growth of TSM was reportedly stymied by the “delicate issue of shifting highway revenues to transit expenditures... [because while] transit theoretically has had legal access to an increasing share of highway trust fund dollars since 1973, ...[actual] transfers are still quite [rare]” (Ferguson 1999, 62). Nonetheless, TDM’s intellectual foundation was thus established through evolving ideas and developments in traffic management strategies, though ‘TDM’ was not used to describe these efforts at that time (Meyer 1999, 582).

2.3.1.2 Energy Conservation

One of the largest policy motivators for managing transportation demand was undoubtedly the energy crises of the 1970s. The 1973 Arab oil embargo and the 1979 Iranian revolution led to
sharp increases in the price of fuel in the US and highlighted the problem of American dependence on foreign oil. These events resulted in unprecedented fuel shortages, hoarding of gas supplies, and long lines at gas stations nationwide (Council on Foreign Relations 2021).

Realizing that transportation activities were exceptionally vulnerable to energy shocks, many metropolitan areas and agencies developed contingency plans for periods of fuel scarcity. Some plans considered actions such as encouraging flexible work hours to reduce demands on transit and road networks, and ridesharing to reduce gasoline usage (U.S. Department of Transportation 1979). At the federal level, the Nixon administration moved to reduce petroleum consumption via a flurry of actions, including the Emergency Highway Energy Conservation Act (1974) which mandated 55 mph speed limits on public highways. This Act and the subsequent Federal-Aid Highway Amendments (1974) allowed states to spend highway funds from the Federal Highway Administration on carpool demonstration programs, with the aim of conserving fuel, decreasing rush-hour traffic congestion, and improving air quality. This was effectively the first instance of federal funding and support for ridesharing (MIT “Real-Time” Rideshare Research Project 2009). Carpool projects eligible for funding included “measures to locate potential carpool riders, buy necessary traffic control devices, and designate existing highway lanes and parking areas for preferential carpool use” (U.S. Congress 1974).

Prior to 1973, organized carpooling activity was reportedly minimal, informal, and private-sector oriented for reasons other than energy conservation. By 1973, half of the 278 urban areas in the US had some form of organized carpool program (Ribner 1981, 61). Carpooling reached the peak of its popularity during this era. However, as gas prices stabilized and became affordable again in the 1980s and 1990s, commuters overwhelmingly returned to driving alone. These shifts
in behavior occurred even though many ambitious programs to promote carpooling were being put into place at the time (Ferguson 1997, 351).

2.3.1.3 Air Quality

Policy actions targeting the connection between air pollution and cars began in the 1950s, following California researcher Arie Jan Haagen-Smit’s unnerving findings that vehicular tailpipe emissions of hydrocarbons and nitrogen oxides were a major cause of smoggy skies over Los Angeles (California Institute of Technology 2013). California set the first tailpipe emissions standards in 1959, and federal emissions standards followed in 1965 (Currie 1979, 815-816).

A major milestone was achieved with the passage of the Clean Air Act (1970), which directed the federal Environmental Protection Agency (EPA) to set National Ambient Air Quality Standards (NAAQS) for six pollutants. Under this Act, all states had to submit plans for meeting these standards. Urban areas which were unlikely to achieve these standards had to develop air quality implementation plans which could consist of stationary or transportation related measures (Greenwald 2019, 13). The EPA was also required to propose and promulgate substitute provisions for disapproved State transportation plans by late 1973, which it did by creating new transportation control measures (TCMs) for some of the largest cities in the US such as Los Angeles, Boston, Dallas and Denver (U.S. Environmental Protection Agency 2016). For example, in the California cities where auto-related air pollution was considered among the worst in the nation, transportation controls included parking restrictions and surcharges, exclusive bus use on some streets, special treatment and bypass lanes for buses and carpools, a mass transit incentive plan by employers, and so on (U.S. Environmental Protection Agency, n.d.). Nonetheless, the public balked at some of the more stringent vehicle restrictions, and Congress subsequently repealed EPA’s authority to curtail automobile travel.
Further Clean Air Act Amendments (CAAs) followed in 1977 and 1990, with greater emphasis on the importance of transportation control measures in meeting air quality standards (Greenwald 2019, 13). In conjunction with the 1977 CAAA, US DOT and EPA issued joint planning guidelines for State Implementation Plans (SIPs); if states could not show attainment with air quality targets, urban areas were required to implement TCMs to reduce emissions to the levels needed. The 1990 CAAA mandated the same, and also refined its list of TCMs. Of the latter, a significant portion could be categorized as aiming to discourage vehicle use (i.e. trip reduction ordinances and reduction of event-related SOV trips), encourage alternatives to driving alone (i.e. improved public transport and ridesharing facilitation), or reduce travel demand (i.e. employer-based transport demand management and flexible work scheduling) (Hall 1995, 95). Thus, managing transportation demand became a part of policy efforts to improve air quality in the US.

2.3.2 The Emergence of TDM as a Concept

Looking back, it is clear that the mix of policy frameworks and actions which came and went or evolved over time – i.e. TSM (transportation system management) actions for improving system efficiency, carpooling programs for conserving energy, and TCMs (transportation control measures) for regulating air quality – were related to each other and found common ground in the concept of managing transportation demand. Interestingly, Ferguson (1999, 67) argues that "the birth of TDM as a concept can be traced with remarkable accuracy to Southern California in 1985... [where] the first written use of the term ‘transportation demand management’ was in the title of a one-year, 12 college equivalent unit (CEU) professional development certificate short course.” The first reference to TDM in periodical literature was then spotted in a 1987 issue of Planning magazine (Fulton 1987), and the first published reference to TDM in federal documents appeared in 1988. Both documents were originally published by Southern California’s regional ridesharing
Several years after the birth of TDM as a concept, TDM became increasingly integrated into transportation planning processes and federal transportation initiatives. In particular, the 1991 Intermodal Surface Transportation Efficiency Act (ISTEA) required metropolitan transportation plans to incorporate demand management actions “to enhance mobility including such things as ridesharing, pedestrian and bicycle facilities, alternative work schedules, high occupancy vehicle treatments, telecommuting, public transportation improvements, road pricing, and intelligent transportation systems” (Meyer 1999, 585). ISTEA also required each designated transportation management area – namely all urbanized areas over 200,000 persons and any additional areas upon request – to have a congestion management system in place. The latter was meant to “[provide] for effective management of new and existing transportation facilities eligible for funding under this title and the [Federal Transit Administration (FTA)] through the use of travel demand reduction and operational management strategies” (Mineta 1991). In addition, ISTEA created the Congestion Mitigation and Air Quality (CMAQ) program to fund transportation projects towards the attainment of air quality standards; eligible projects included those listed in an approved SIP and/or TCM as per the 1990 CAAA (Meyer 1999, 587).

After ISTEA, the 1999 Transportation Equity Act for the 21st Century (TEA-21) continued many of ISTEA’s demand management initiatives. More recent federal regulations like the 2012 Moving Ahead for Progress in the 21st Century Act (MAP-21) and the 2015 Fixing America's Surface Transportation Act (FAST) also “[endorsed] the integration of multi-modal alternatives and TDM concepts into America's transportation planning process” (Greenwald 2019, 15). With these developments, it appears that TDM principles have since become institutionalized in transportation planning processes across the US, especially for urban areas.
2.4 Transportation Demand Management in the Private Sector

2.4.1 Early Efforts and Drivers of Private Sector TDM

At first glance, the literature described above appears to suggest that the idea of TDM was by far and large the brainchild of government policymakers and transportation planners. However, TDM at the private sector level has had a long history of its own, leading to what is now commonly called “employer-based TDM” or the “employee commute options” programs of today.

Schreffler (1983, 45) notes that initial workplace-based TDM efforts, such as ridesharing, were likely employee-led and involved informal arrangements with coworkers and neighbors. That said, some employers took it upon themselves to organize or provide for commuting alternatives to driving alone. One such example involves Reader's Digest in the late 1920s, whose headquarters was located in a suburb that was 50 miles north of New York City and served by limited public transportation. Reader’s Digest offered subsidized chartered bus services costing about 20 cents a ride, between its headquarters and surrounding communities, to attract and recruit employees who would otherwise find their commute to be inconvenient (Lowe 1981, 73).

However, it was not until World War II (and the resulting resource shortages) that large-scale efforts to promote workplace-based carpooling were put into place. Many employers set up carpool matching services for employees, and some workplaces were noted for providing a variety of incentives to carpoolers. These included “supplemental gasoline coupons, tire allocations, permits for re-caps, preferential parking of various types, lapel buttons, windshield stickers for recognition, and special insurance coverage for carpools” (Ribner 1981, 62). During this period, more commuters travelled in carpools compared to all other forms of mass transit. That said, after World War II, interest in ridesharing declined due to the boom in suburban growth, rising prosperity and corresponding increases in automobile ownership (Pratsch 1975).
By the late 1960s and early 1970s, interest in addressing employee commute issues was revived among several major employers who then made headlines for their innovative offerings (Schreffler 1981, 47-49). For example, organized vanpooling was pioneered by 3M, which went from 6 vans in early 1973 to 100 vans by 1979; this model was adopted by employers nationwide inclusive of Fortune 500 companies (Sears 1979, 1-2). With the energy crises of 1973-1974 and 1979, more employers adopted strategies such as subsidizing bus passes, flexi-hour schemes, providing buses and vanpools, and supporting carpooling efforts (Enoch 2012). For example, Lockheed Martin Space Systems Company started a Commutes Alternatives Program in the early 1970s which remains in place till this day (511.org, n.d.).

That said, prior to the energy crises and subsequent government actions, private employers’ reasons to provide or encourage alternative commuting modes were often unrelated to public goals such as energy conservation or air quality improvement. Enoch (2012) observes that employers’ objectives for getting involved – then and now – are not always the same as or even complementary to those of government agencies, but may be more complex. DeHart-Davis and Guensler (2005, 680-682) theorize that employers’ willingness to voluntarily support commute options are affected by one of three motivations: (i) organizational self-interest (in the case of a perceived direct or indirect economic payoff), (ii) organizational control (where actions taken compel employee behavior to be more closely aligned to the organization's goals), and (iii) association membership (where members conform to peer norms to gain the approval and respect of fellow members).

As evidenced from literature reviews of the subject, these kinds of motivations have surely come into play among employers then and now. For example, researchers writing about employer-based commuter transportation in the 1960s and early 1970s noted that some employers considered providing and promoting these commute alternatives as a preferred solution for parking shortages.
To these employers, this strategy was cheaper and more worthwhile as opposed to (i) building new parking facilities that might cost millions of dollars, take up potential office space and limit the employer’s ability to expand on-site, and/or (ii) paying for costly street parking after having moved or consolidated their offices to a downtown location. Other reasons for employer involvement included: (i) wanting to reduce on-site traffic congestion associated with driving and parking, and (ii) wanting to reduce employee inconvenience, absenteeism and lack of punctuality e.g. in cases of bad weather which might affect employees’ commutes. In some cases, companies provided commuter transportation alternatives as a public relations exercise to enhance their community image. Some employers offered these arrangements to compensate for recruitment and retention problems associated with suburban workplace locations, where employees might be demotivated by long, slow or congested commutes, and limited or non-existent public transportation services (Lowe 1981; Misch et al 1981; Ribner 1981; Schreffler 1983; Sears 1979). With the energy crises of the 1970s, another reason for employer involvement was to ensure that employees could get to work reliably in case of a fuel shortage (Misch et al 1981).

With the 1973 energy crisis, what had been arguably a largely private sector response began to be noticed by the public sector. The Federal Highway Administration (FHWA) began cataloging successful employer ride-matching programs to publish guidebooks on carpooling and vanpooling. FHWA’s nationwide survey results indicating that employee carpooling helped to decrease vehicle miles travelled (VMT) led to the federal government’s 1974 funding authorization for rideshare demonstration projects across various metropolitan areas (Chan and Sheehan 2012, 100-101). Policymakers concluded that TDM initiatives needed support and cooperation from the business community to be successful, even surmising that “perhaps the best mechanism for implementing work-trip TDM actions was through employers” (Meyer 1999, 577). Meanwhile, regulations were
developed to influence and even mandate TDM initiatives among employers via a mix of “carrot and stick” approaches. Two of the most pertinent legislative actions which are still practiced today – namely employer-based trip reduction and commuter benefits – are discussed below.

2.4.2 **Employer Based Trip Reduction**

Employer-based trip reduction (EBTR), where mandated by law, has arguably constituted more of a “stick” approach where employer participation is a must and noncompliance is penalized by the authorities. Initially, trip reduction ordinances (TROs) emerged in the early 1980s and grew in number at local and regional levels, prior to attempts to implement them federally. One of the first TROs was launched in Pleasanton, California in 1984, which ambitiously moved to limit peak-hour solo driving to no more than 55% of the daytime workforce; employers with 100 or more employees were required to meet this standard by any means including carpooling (U.S. Environmental Protection Agency 1992, 2). Meanwhile, the largest mandatory EBTR program was instituted in 1988 via the Southern California Air Quality Management District's Regulation XV, which affected over 2.26 million employees or 40 percent of SCAQMD’s 5.4 million workers. Regulation XV’s goal was to achieve National Ambient Air Quality Standards (NAAQS) by 2010 by requiring employers to meet a minimum average vehicle ridership (AVR) of 1.5 persons for most of the urban and suburban region; it set out to do so by mandating that any company with over 100 employees employ a trained Employee Transport Coordinator to help meet targets set by a Trip Reduction Program (Chan and Sheehan 2012, 103). These local and regional legislative attempts culminated in the federal-level Employee Commute Options (ECO) requirement of the 1991 Clean Air Act Amendments. The ECO sought to compel work sites with 100 or more employees in the most polluted cities nationwide to implement ridesharing programs and also submit annual trip reduction plans (Wachs and Giuliano 1992). However, such a heavy-handed
regulatory approach focused on trip reduction was found to be costly to the regulated parties and created widespread backlash. The general unpopularity of these initiatives led to Regulation XV’s repeal and the ECO section of the CAAA being made voluntary in 1991 (Enoch 2012).

Today, there are no federal laws to mandate trip reduction among employers, though a smattering of such regulations still exists at state and local levels. Examples include Washington’s large-scale, mandatory Commute Trip Reduction Efficiency Act, for worksites with 100 or more employees in the state’s nine most populous counties; Oregon’s mandatory Employee Commutes Program, for employers with 100 or more employees in Portland and surrounding areas; and, in Arizona, Maricopa County’s Travel Reduction Program (TRP) ordinance for employers with a minimum of 50 employees (Maricopa County 2021; Oregon Department of Environmental Quality, n.d.; Washington State Department of Transportation, n.d.). With Maricopa County, for example, its ordinance today requires that an employer (i) appoint a transportation coordinator, (ii) conduct an annual survey to help determine the rate of single-occupancy vehicle (SOV) trips and rate of single-occupancy vehicle miles traveled (SOVMT) for each work site, and (iii) implement and document a travel reduction plan to assess whether requirements have been met, which will be monitored by Maricopa County TRP staff within the plan year. The travel reduction plan in question must indicate the measures that the employer plans to use, drawn from one or more categories i.e. (1) participation incentive drawings, (2) subsidy and rideshare provisions, (3) alternative work schedules and locations, (4) physical amenities, (5) electric vehicle charging stations, (6) equivalent emissions reduction measures, and (7) other TRP measures. Employers who fail to comply with or meet requirements face potential civil penalties and fines – up to $300 a day – in addition to any expenses incurred by the employer to fully execute the approved plan (Maricopa County 1994; Maricopa County Air Quality Department 2021).
2.4.3 Commuter Benefits

Commuter benefits rely on a “carrot” approach for employers and employees, whereby the former offers the latter financial benefits for qualifying alternative commuting modes. Commuter benefits can be provided in three ways: (i) employer-paid, where the employer pays either a portion of employees’ costs or the full cost, (ii) employee-paid, where the employees pay for the expenses themselves using pre-tax income via payroll deduction, and (iii) a combination of options (i) and (ii) where the employer and employee share payment for commuting expenses. For both parties, the “carrot” is not having to pay federal payroll taxes or income taxes on the benefit (National Academies of Sciences, Engineering, and Medicine 2005, 6).

Under the federal tax code, commuter benefits are officially termed qualified transportation fringe benefits and are not considered wage or salary compensation (as mentioned in the Internal Revenue Code Section 132(f)) (Best Workplaces for Commuters 2013, 4). These tax benefits were first introduced in the Tax Reform Act of 1984, where Congress made employer-provided parking fully exempt from taxable income and allowed employer-paid transit benefits of up to $15 monthly to be tax-free. The policy discussion during that time was not focused on transportation impacts but rather on the implementation of tax policies and their impacts on US workers. Nevertheless, the scope of tax benefits for alternative modes of transportation has been expanded since then, to the advantage of alternative commute mode users. For example, the 1992 Energy Policy Act grouped parking and transit benefits together into ‘qualified transportation fringe benefits’, made vanpools eligible, capped amounts excludable from taxable income at $150 for parking and $60 for transit a month, and made these amounts adjustable for inflation (Transportation Policy Research Center 2015, 2). In 1998, the Transportation Equity Act for the 21st Century (TEA-21) “expanded the commuter benefit so that employers could offer transit and vanpool benefits in lieu...
of and in addition to wages, options already allowed for parking. This meant that the commuter tax benefit could be offered as a pre-tax employee-paid benefit” (Transportation Policy Research Center 2015, 2). After 1991, the amount limits for employer-paid tax-free transit and vanpool benefits were raised several times. In 2009, Congress temporarily raised the amount limits on transit and vanpool benefits to be on par with the parking benefit, at $230 a month. This state of parity for transit, vanpool and parking benefits was temporary at first, and between 2009 and 2015 Congress regularly extended this parity as part of an annual or biennial arrangement, before it finally made parity permanent with no expiration date (LattaHarris LLP 2016). From 2009 through 2018, employers could also reimburse employees up to $20 per month tax-free for eligible bicycle expenses (albeit unadjusted for inflation), though the 2017 Tax Cuts and Jobs Act made this benefit taxable to employees from 2018 through 2025 (Best Workplaces for Commuters, n.d.).

Although employer provision of commuter benefits is largely voluntary, some jurisdictions have begun mandating them via commuter benefits ordinances. San Francisco enacted the first such municipal ordinance in 2009, and New Jersey was the first state to sign a statewide ordinance in March 2019 (EPIC Insurance Brokers and Consultants 2020). These ordinances generally compel employers of a certain size to provide commuter benefits to their employees, via one or more of the following options: (i) employee-paid pre-tax benefits, (ii) employer-paid direct benefits, and/or (iii) employer-provided transportation. Options (i) and (ii) are very much in line with the Internal Revenue Code Section 132(f)’s allowances for pre-tax and direct benefits. For example, Washington D.C.’s Commuter Benefits Law as applied to the year 2019 requires companies of at least 20 employees to (i) allow employees to elect to set aside up to $265 from their paycheck each month for transportation in a commuter highway vehicle, a transit pass, or beginning in 2026, commuter bicycling costs; (ii) at the employee's election, supply a transit pass
or reimburse the employee for vanpool costs, up to $265 per month; and/or (iii) provide transportation such as a shuttle, vanpool, or bus operated by or for the employer at no cost to employees. Any D.C. employer that fails to offer at least one option will face penalties. Except for bicycle commuting reimbursements prior to 2026, the value of the commuter benefits is not includable in an employee's taxable income (Wright et al 2019).

In essence, ordinances mandating either commuter trip reduction or commuter benefits rely on the same types of tools for success – namely employers’ provision of subsidies, amenities, and other support mechanisms to help employees choose alternative commute modes. However, such laws requiring these initiatives are still the exception rather than the norm.

2.5 Employer-Based TDM and Commute Options Programs Today

2.5.1 Best Practices and Common Offerings

Today, if an employer provides amenities, mechanisms and/or financial benefits to enable and support alternative commuting, these offerings are often referred to collectively as a ‘commute options program’ (Massachusetts Department of Transportation, n.d.) Though offerings for each commute options program vary among employers, the National Standard of Excellence for commuter benefits offers a ‘gold standard’ benchmark for best practices and comparison purposes. This benchmark was first created by the US Environmental Protection Agency (EPA) and US Department of Transportation (DOT) in 1999, and was known then as the Commuter Choice Leadership Program. The program has since been rebranded as the Best Workplaces for Commuters (BWC) program, and is managed by the National Center for Transit Research at the Center for Urban Transportation Research which is based at the University of South Florida (Best Workplaces for Commuters, n.d.). Any employer that offers a commuter benefits package which
meets the standards for a particular year becomes a member of that year’s BWC list. To qualify for the BWC list in 2021, employers had to meet the following standards listed on its website:

“Must offer at least one (1) of the following Primary Benefits:

- At least $30 per month towards a transit pass.
- At least $30 per month for vanpool pass (or the full cost of a pass if it is less than $30) to each employee who commutes using transit or a vanpool.
- Provide a pre-tax option for employees to purchase a transit pass and/or vanpool pass with at least 30% of employees purchasing such fare media of at least $30 per month;
- A significant telework program that reduces by at least 6% the number of motorized vehicle trips employees make per week.
- A significant compressed work week program with employees working longer hours on fewer days that reduces by at least 6% the number of motorized vehicle trips our employees make per week.
- A parking cash out option to employees. Parking cash out is a program that allows employees to opt out of having an employer-subsidized parking space and instead, receive compensation. Offer to pay employees at least $30 per month (in lieu of providing a parking spot) to each employee who leaves their car at home and commutes another way.
- Fully or partially fund one or more employee shuttles from rail stations and/or park and ride lots. The shuttles can either be directly operated by the employer or purchased transportation through a local TMA or service provider.
- A significant bicycle commuting program with at least 6% reduction in the number of motorized vehicle trips our employees make per week.
Pay at least $30 per month to employees to **carpool** to work that reduces by at least 6% the number of vehicle trips our employees make per week.

An **equivalent benefit** that provides similar value to employees, reduces traffic and air pollution, and is agreed to by Best Workplaces for Commuters.

Your organization must also offer employees access to an Emergency Ride Home program and three supporting benefits, such as carpool matching, electric vehicle recharging stations, and on-site amenities (e.g., cafeteria, dry cleaners). If you have fewer than 20 employees, you need only provide one supporting benefit. Your organization must agree to work towards a goal of 14% or more of employees NOT driving to work alone, and agree to a membership dues of $250 per worksite (multiple worksite discounts are available) that directly provides support to the program managed by the Center for Urban Transportation Research at the University of South Florida with support from members, partnering organizations, the National Center for Transit Research at USF and the Florida Department of Transportation. The membership dues for Florida employers is sponsored by the Florida Department of Transportation” (Best Workplaces for Commuters 2021).

Figure 1 below shows the most common types of primary benefits offered by BWC-qualified employers. The top two benefits most offered are telework and transit pass subsidies.
Figure 1: Primary Benefits Offered by BWC-Qualified Employers (Source: Best Workplaces for Commuters, n.d.)

Figure 2 and Figure 3 show the most common types of primary and secondary benefits respectively offered by large employers in the BWC member list (with over 1,000 employees).

**Large Employers (over 1000) – Primary Benefits**

- $80 = Average transit pass subsidy (n=30)
  - $200 = Maximum transit pass subsidy
- $118 = Average vanpool pass subsidy (n=16)
  - $265 = Maximum vanpool pass subsidy
- 45% offer pre-tax purchase of transit/vanpool fares
- 63% offer telework with at least 6% trips reduced
- 16% offer compressed work weeks
- 45% offer shuttle for employees
- 27% offer bicycle benefit

Figure 2: Primary Benefits Offered by BWC-Qualified Large Employers (Source: Best Workplaces for Commuters, n.d.)
As shown in the figures above, this sampling of BWC-qualified employers is small and represents a snapshot of best practices at some rather than the majority of employers. For a larger sampling of employers, the annual Employee Benefits Survey conducted by the Society for Human Resource Management (SHRM) offers a helpful perspective. SHRM’s 2019 survey (which is the most recent version available for public download) involved 2,763 HR professionals across the US who were randomly selected and asked about their company’s benefits. Interestingly, where transportation-related benefits are concerned, the survey findings show that transit subsidies and transportation spending accounts (i.e. commuter benefits) were offered far less often compared to free on-site parking amenities or even subsidies for personal vehicles (see Figure 4 below) (Society for Human Resource Management 2019). These findings suggest that there is a long way to go before employee commute programs become part and parcel of employer benefit offerings.
2.5.2 Factors Affecting Success for Employee Commute Options Programs

On the question of what makes employer-based TDM initiatives effective (or not), academic and professional literature, as well as TDM guidebooks produced by public authorities, can help to lend some crucial insights.

The Massachusetts Department of Transportation, in its *Guidebook to Implementing An Employer-Based Commutes Program*, cautions that “which strategies are most appropriate and effective for your workplace depends on several factors, including land-use mix and density, transit access, availability of bike and pedestrian facilities and shared-use mobility providers” (Massachusetts Department of Transportation, n.d., 9). In other words, there is not a one-size-fits-all strategy that can guarantee success, and the strategies adopted ought to be carefully chosen with the characteristics of the worksite in mind (i.e. local topology, infrastructure and available transportation services). The Guidebook identifies five types of topologies and describes their conditions, as well as limitations, as per Table 1 below.

![Figure 4: Frequency of Transportation Benefits Offered Among Organizations Surveyed in SHRM’s 2019 Employee Benefits Survey (Source: Society for Human Resource Management 2019, 7)](image)

<table>
<thead>
<tr>
<th>Transportation</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free onsite parking</td>
<td>88%</td>
<td>84%</td>
<td>83%</td>
<td>85%</td>
<td>83%</td>
</tr>
<tr>
<td>Subsidy for business use of personal vehicles</td>
<td>31%</td>
<td>22%</td>
<td>23%</td>
<td>22%</td>
<td>30%</td>
</tr>
<tr>
<td>Company-owned vehicle for business and personal use</td>
<td>18%</td>
<td>20%</td>
<td>22%</td>
<td>21%</td>
<td>22%</td>
</tr>
<tr>
<td>Transit subsidy</td>
<td>13%</td>
<td>13%</td>
<td>13%</td>
<td>13%</td>
<td>14%</td>
</tr>
<tr>
<td>Qualified transportation spending account</td>
<td>14%</td>
<td>10%</td>
<td>11%</td>
<td>12%</td>
<td>12%</td>
</tr>
<tr>
<td>Parking subsidy (either onsite or offsite)</td>
<td>10%</td>
<td>10%</td>
<td>10%</td>
<td>12%</td>
<td>12%</td>
</tr>
</tbody>
</table>

* Tax-advantaged savings plan designed to encourage saving for future college costs
Table 1: Typology Identification for Implementing Commute Options Programs (Adapted from Massachusetts Department of Transportation, n.d., 9)

<table>
<thead>
<tr>
<th>Typology Name</th>
<th>Land Use / Parking</th>
<th>Transportation Infrastructure/ Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Core/Inner Suburbs</td>
<td>• The Urban Core/Inner Suburbs typology features a mix of commercial and residential land uses a large number of employers and a wide variety of employer types.</td>
<td>• Multiple forms of frequent transit are available in the urban core and inner suburbs.</td>
</tr>
<tr>
<td></td>
<td>• Parking tends to be expensive and limited, particularly in central business districts.</td>
<td>• Sidewalks and pedestrian crossings make it easy to walk.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Bike infrastructure features good connectivity and is well utilized.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• In central business districts, carshare, bikeshare and other shared-use mobility providers offer additional transportation options.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Outside of central business districts, shared mobility options are available, but not as widespread.</td>
</tr>
<tr>
<td>Gateway City</td>
<td>• The Gateway City typology describes mid-size urban centers that anchor the regional economy.</td>
<td>Gateway cities may be serviced by a reliable bus network, but there are fewer routes and service is not as frequent as in the urban core/inner suburbs.</td>
</tr>
<tr>
<td></td>
<td>• They feature a mix of commercial and residential land uses and employer types.</td>
<td>Gateway cities usually have good sidewalk coverage in the city center, but limited bike infrastructure. Carshare and bikeshare may exist, but typically not with wide coverage.</td>
</tr>
<tr>
<td></td>
<td>• Parking is usually free or very inexpensive.</td>
<td></td>
</tr>
<tr>
<td>College Town</td>
<td>• This typology describes small to medium-sized towns that are hosts to at least one college or university.</td>
<td>College towns typically have better bike and pedestrian infrastructure than other towns of the same size.</td>
</tr>
<tr>
<td></td>
<td>• They feature a mix of commercial and residential land uses and employer types.</td>
<td>They are served by transit that tends to run relatively infrequently (hourly).</td>
</tr>
<tr>
<td></td>
<td>• Parking is usually free, but can be limited around the college/university.</td>
<td>In some cases, more frequent transit runs on routes serving the college or university.</td>
</tr>
</tbody>
</table>
Table 1 Continued

<table>
<thead>
<tr>
<th>Office Park</th>
<th>Rural</th>
</tr>
</thead>
<tbody>
<tr>
<td>• The office park typology describes a collection of buildings usually occupied by several employers.</td>
<td>• Office parks tend to have good highway or state route access, but transit is often more than one mile away.</td>
</tr>
<tr>
<td>• Land uses are exclusively commercial and dominated by worksites, but can also include retail or industrial/warehousing.</td>
<td>• They typically lack bike and pedestrian infrastructure.</td>
</tr>
<tr>
<td>• There is plenty of free surface parking.</td>
<td>• There is little or no access to transit and typically no or very limited active transportation options.</td>
</tr>
</tbody>
</table>

In addition, different strategies have their own considerations and challenges which affect success rates once they are implemented. These issues are detailed below by mode, in the following order: (i) transit, (ii) active commuting, (iii) ridesharing, and (iv) alternative work hours.

2.5.2.1 Transit

A common strategy for increasing transit use involves offering transit benefits, which act to subsidize transit pass costs. However, a report titled *Analyzing the Effectiveness of Commuter Benefits Programs*, produced by the Transit Cooperative Research Program (TCRP) and sponsored by the Federal Transit Administration, concludes that “There is no one simple rule of thumb to estimate what, if any, increase in transit use and reduction in vehicle travel will occur as the result of a transit benefits program” (National Academies of Sciences, Engineering, and Medicine 2005, 10). Having analyzed 21 surveys from transit/commuter organizations conducted in 12 regions from 1989 to 2004, the report found that transit ridership generally increased at participating
worksites after a transit benefits program was implemented, but the percentage increase in transit use varied dramatically among regions and individual worksites. The report observed that the largest increases in transit use typically occur in urban locations where transit services are available, while conversely “no change in transit use may be expected in suburban areas with very limited transit services.” Interestingly, the report suggests that “some employer-based commuting programs, like ridesharing or telework programs, may also compete against transit benefit programs” since there is only a finite market of potential “switchers” who may find the other options more attractive than transit. Parking, especially when free or subsidized by employers, is also considered a threat to transit attractiveness. Based on these findings, the report concludes that a variety of factors go into determining the success rate of a transit benefits program in converting drive-alone commuters to transit (see Figure 5 below).

![Figure 5: Factors that Affect Transit Ridership Levels with Implementation of a Transit Benefits Program (Source: National Academies of Sciences, Engineering, and Medicine 2005, 11)](image-url)
In other words, the availability of transit benefits is not the only deciding factor and does not address the issue of whether transit services are available and accessible to begin with. TCRP’s Transit Capacity and Quality of Service Manual (TCQSM) argues that transit availability involves several aspects: spatial availability at origin and destination, information availability, and temporal availability (National Academies of Science, Engineering, and Medicine 2013, 3-13). If any of these needs are not fulfilled, transit is not a viable option. This is detailed in Figure 6 below.

![Figure 6: Transit Trip Decision-Making Process: Transit Availability (Source: National Academies of Science, Engineering, and Medicine 2013, 3-13)]
Other service-related factors that may influence commuters’ perceptions of and willingness to use transit are service coverage, scheduling, transit information, transfers, total trip time, cost, safety and security, passenger loads, appearance and comfort, and reliability (National Academies of Science, Engineering, and Medicine 2013). TCRP’s 2018 research report titled *Understanding Changes in Demographics, Preferences, and Markets for Public Transportation* – which used an integrated travel demand model on thousands of survey results from across the nation – firmly concluded that “improving transit service has a much larger impact on transit use than does having a population with the attitudes, preference and demographics of the most pro-transit among us.” The research analyzed the results of two surveys – one conducted on 11,000 residents in 46 metropolitan areas in 2014, and the other conducted on 3,500 residents in 24 metropolitan areas in 2016 – and found that across all age groups, concerns about travel time and reliability were rated as more important than frequency or proximity when it came to issues of service quality (National Academies of Science, Engineering and Medicine 2018, 25).

In terms of access to transit from one’s starting location, studies suggest that most people are willing to walk for five to ten minutes, or approximately ¼ to ½ a mile to a transit stop, although they may be willing to walk considerably further to access heavy rail services. Bicyclists are also willing to ride far further than ½ a mile to access rail stations (U.S. Department of Transportation 2013). That said, acceptable walking distances can vary due to: (i) demographics, namely whether travelers are transit-dependent or discretionary users, (ii) walkability, whereby better walking conditions such as good sidewalks, minimum waits at crosswalks, and attractive and secure landscapes encourage people to walk further, and (iii) transit service quality, whereby people tend to walk further if transit service is frequent, and vehicles and stations are comfortable and attractive (Litman 2021, 35).
2.5.2.2 Active Commuting

The US Department of Transportation’s *A Guidance Manual for Implementing Effective Employer-based Travel Demand Management Programs* observes that biking and walking are limited somewhat by geography, climate, commute distances and employee lifestyle. The site and employee characteristics that most favor these modes include: (i) short-distance commutes (five miles or less for bicycling and two miles or less for walking), (ii) relatively flat terrain in the area of the worksite, (iii) mild temperatures and dry climate, and (iv) safe commuting paths (i.e. low traffic volume roads, bikepaths, and sidewalks) (U.S. Department of Transportation 1993, 13-14). A study of bicycle commuters in the Washington, D.C. area by Buehler (2012) found that the odds for cycling to work are greater for employees with access to both cyclist showers and bike parking at work compared to those with just bike parking, but no showers at work. The study also found that free car parking at work is associated with 70% smaller odds for bike commuting (Buehler 2012). Likewise, other studies have found that workplaces which limit or charge for car parking, offer free off-site parking, have parking lots at a distance, and have free or low-cost recreation facilities nearby are also associated with increased active commuting (Bopp et al 2016; Panter, Desousa, and Ogilvie 2019).

2.5.2.3 Ridesharing

Here, ridesharing comprises carpooling and vanpooling. Best Workplace for Commuters’ guidebook on carpool incentive programs cautions that “although any employer can encourage carpooling, carpooling is more likely to be successful in certain cases.” According to Best Workplaces for Commuters, these cases are: (i) regions with dedicated high-occupancy vehicle (HOV) lanes which may reward commuters with time savings and sometimes financial savings (in areas where carpool lanes are used at toll lanes), (ii) employers with limited parking, (iii)
employers with large numbers of employees, so that it becomes easier to find a convenient match, and (iv) employers in urban settings, since it is theoretically easier to find a convenient match in higher-density employment settings even outside the company (Best Workplaces for Commuters 2005, 4-5). The US Department of Transportation’s A Guidance Manual for Implementing Effective Employer-based Travel Demand Management Programs also suggests that the following site and employee characteristics favor ridesharing success: (i) consistent work hours, (ii) residential concentrations of employees, (iii) high percentage of employees with commutes longer than 10 miles or 20 minutes, (iv) high percentage of employees with low to moderate salaries, (v) availability of nearby HOV lanes, and (vi) constrained parking supply (U.S. Department of Transportation 1993, 12-13). A newer version of this manual suggests that compared to the typically shorter distances travelled by carpools, vanpools “tend to work best for commutes of at least 25 miles or more each way” (U.S. Department of Transportation 2003, 15).

That said, a lack of matching schedules among employees can be a major barrier to carpooling; employees who carpool together must generally arrive and depart at the same time or the carpool arrangement will prove inconvenient (Best Workplaces for Commuters 2005, 5-6). The principal disadvantage of requiring riders to commit to a common schedule is magnified for vanpooling, since vanpools usually involve seven to 15 employees commuting together as opposed to just two or more employees in a carpool (U.S. Department of Transportation 1993, 12-13).

2.5.2.4 Alternative Work Hours

Per the US Department of Transportation’s A Guidance Manual for Implementing Effective Employer-Based Travel Demand Management Programs, alternative work hour arrangements fall into four general categories: (i) staggered work hours, (ii) compressed work weeks, (iii) flexible work hours, and (iv) telecommuting. These options differ from the conventional alternative modes
of taking transit, carpooling or active commuting via biking and walking, inasmuch as they concern the timing of commute trips rather than the mode of transportation (U.S. Department of Transportation 1993, 14-17). The likelihood of using alternative work hour arrangements depends on the employer’s approval, and whether these arrangements suit the workplace in question.

One question that arises is whether alternative work hour arrangements help to support the use of alternative modes and therefore reduce vehicle trips. The Transit Cooperative Research Program (TCRP)’s 2010 report titled *Employer and Institutional TDM Strategies* observes that “alternative work arrangements that allow employees to synchronize their work schedules with the demands of an alternative mode are designed to explicitly encourage alternative mode use.” However, it cautions that policies which allow employees to shift travel outside of peak hours, compressed work weeks, and telecommuting may inadvertently detract from alternative mode use and reinforce drive-alone habits. This may happen in some cases where alternative work hour arrangements reduce the stresses of driving in peak-period traffic, or where ridesharing or transit trips to the workplace are difficult to arrange in line with an alternative work hour schedule (National Academies of Sciences, Engineering, and Medicine 2010, 19-62 to 19-63).

### 2.5.3 Impacts Associated with Various TDM Strategies

To evaluate the impacts of various TDM strategies, TCRP’s report on *Employer and Institutional TDM Strategies* examined 82 cases in which “before” and “after” data is available (National Academies of Sciences, Engineering, and Medicine 2010). Though the report dates from 2010, the employer case studies which were analyzed are much older, i.e. from the early 1990s; more recent data was found to be unsatisfactory in terms of analytical rigor and was thus discarded. The report found that on average, impacts of 4% to 5% site-specific vehicle trip reduction (VTR) were achieved due to employer support programs such as commuter information services,
employee transportation coordinators, rideshare matching, transportation fairs, on-site transit pass sales, and guaranteed ride home. The following conclusions were drawn for specific strategies:

- **Guaranteed ride home** impacts ranged from nil to upwards of 5% VTR. That said, empirical quantitative data on its impacts were scarce and not sufficiently informative;

- **Employer transportation services** (such as employer assistance with vanpool creation and program management, transit assistance in the form of running separate shuttles or contracting with the transit operator to intensify service, or allowing use of company vehicles for ridesharing or midday business trips) helped to achieve as much as 22% VTR on average. In contrast, employer-based TDM programs which did not provide these services achieved 14% VTR on average;

- **Modal subsidies** (i.e. financial incentives linked to alternative modes), when combined with employer transportation services, helped programs to achieve just under 27% VTR on average. In contrast, programs which provided employer transportation services but did not provide modal subsidies achieved slightly over 9% VTR on average;

- **Good transit availability** enabled worksites to realize an average VTR rate of 26% versus 12% at worksites without good transit;

- **Worksites that offered a transit subsidy** averaged 21% VTR versus 14% among worksites that did not provide a subsidy; and

- **Worksites that offered HOV parking discounts** averaged 26% VTR versus 14% for worksites which did not.

In addition, the combination of parking fees and employer transportation services resulted in a strong synergistic effect, with an average VTR rate of 37% achieved. One such success story is the University of Washington’s U-PASS program, which notably combined parking pricing,
transportation services, and financial incentives; it obtained a 31% VTR rate over 16 years. The report authors concluded that “clearly, if it is more difficult or costly to drive, TDM alternatives become more attractive” (National Academies of Sciences, Engineering, and Medicine 2010, 19-14). That said, the report authors stress that of these 82 cases, “many of the examples were originally selected because they were distinct in some way – often because they were regarded as success stories. Hence, the performance of this group of programs should not be looked upon as being ‘typical’” (National Academies of Sciences, Engineering, and Medicine 2010, 19-11).

2.5.4 The Role of Parking in Employer-Based TDM Strategies

Again and again, studies on employer-based TDM have concluded that the availability of abundant and cheap parking is a major impedance to TDM program success. The abovementioned analysis by TCRP in 2010 found that as a group, 27 programs which offered incentives but had no restrictions on parking had an average VTR of 14.3%, which is more than 7% average VTR for the group of 14 programs which had unrestricted parking and no subsidies, but far less than the 23.3% average VTR for the group of 37 employers who had both restricted/priced parking and offered subsidies. The report concludes that “the supply and price of parking serving a worksite have the single largest effect on the performance of employer-based TDM programs. Not only does limited parking or the existence of parking fees discourage solo driving outright, but such conditions also tend to increase the appeal of travel alternatives and other TDM strategies” (National Academies of Sciences, Engineering, and Medicine 2010, 19-48). Similarly, Hamhre and Buehler’s study of revealed preferences among 4,630 commuters in the Washington, D.C. area, using data from the 2007/2008 DC Household Travel Survey, found that no benefit combination of public transportation benefits and bike/walk benefits which included free car parking was associated with increased odds for riding public transportation, walking or cycling to
work. The study concludes that “benefit combinations that include free car parking either overwhelm or render insignificant the positive effects of benefits for public transportation, walking, and cycling” (Hamhre and Buehler 2014, 83).

2.6 Summary

Overall, even with employer-based TDM initiatives in place, it is clear that there are many situational push-and-pull factors which may attract commuters towards a particular mode choice and deter them from others. As long as parking is free, cheap and/or plentiful, it will be extremely difficult to lure commuters away from driving. That said, even when parking charges or penalties are imposed, a review of program results – i.e. the TCRP 2010 study in which the highest average VTR achieved was 23.3% for a group of 37 employers who had both restricted/priced parking and offered subsidies for alternatives – suggests that many commuters will persist in driving alone even when alternatives are made available. This raises the question of whether the alternative modes are truly competitive against driving.

As it turns out, each alternative mode has its potential drawbacks and barriers, some of which may prove unpalatable or unsuitable for users depending on their individual preferences and lifestyles, where they live (which makes some modes more accessible and available than others), and the costs and penalties of these modes. A key takeaway is that TDM initiatives, despite their noble intentions, still have to grapple with underlying conditions that may be out of their control. The question then is how to assess the underlying market for alternative commutes, determine which options are competitive with the default choice of driving alone, and develop realistic expectations for take-up rates. The next section uses a case study of a major employer in Atlanta, GA and its employees to provide a unique reference point for employer-based TDM practitioners.
CHAPTER 3: CASE STUDY – ATLANTA, GA MAJOR EMPLOYER

The remainder of this research evaluates the feasibility of various alternative commute modes for corporate employees, specifically at a major employer in Metro Atlanta, GA. In theory, the provision of employer-based TDM initiatives should encourage employees to adopt alternatives to driving. However, the reality on the ground may be very different, as employee commuting behavior may be affected by certain geographical and practical constraints. These constraints include employees’ home locations, the availability and accessibility of alternative modes, and whether the switch from driving to another mode is perceived to be worth making.

To better understand the context behind commuting culture featured in this case study, it is necessary to examine the geographical and local conditions in which the employer operates, including transportation supply and service providers in a given geography. The following section discusses Metro Atlanta and the employer’s corporate headquarters there, which is also where the study takes place.

3.1 The Metro Atlanta Landscape

3.1.1 Development and Sprawl

The City of Atlanta is the capital city of the State of Georgia and was founded in 1837 as a railroad terminus. Today, it remains a major transportation hub due to the Hartsfield-Jackson Atlanta International Airport, which is the world’s busiest airport in terms of daily passenger flights. The city also boasts over 1,000 international businesses, representation of over 50 countries through consulates, trade offices and chambers of commerce, as well as the third largest concentration of Fortune 500 companies in the country (City of Atlanta, n.d.). The City of Atlanta covers around 137 square miles (U.S. Census Bureau, n.d.) and is in parts of Fulton and DeKalb.
counties (see Figure 7 below). The city’s population grew 18.7% from 427,059 persons in April 2010 to 506,811 persons in July 2019, giving the city an estimated population density of 3,669.45 persons per square mile in 2019 (U.S. Census Bureau, n.d.).

Figure 7: City of Atlanta and The Core 10-County Metro Atlanta Region (Source: Atlanta Regional Commission, n.d.)

The shaping of the City of Atlanta as it is today began after World War II, when the City annexed 82 square miles of land to accommodate continual industrial and business growth as well as its rapidly expanding population. The City’s post-war development priorities were focused on highway and freeway construction to meet its growing needs, which “allowed the [City] to link up later with three major interstate highways that connected Atlanta to the region and fed suburban metropolitan growth” (Ambrose 2020). Urban renewal was also a priority for city planners and
urban leaders who adopted a “war on density” mindset; their aim was to eliminate slums and modernize the city by clearing large tracts of occupied land for new uses. Generally, the City’s decision-makers “hoped to transform parts of urban residential neighborhoods into commercial or municipal developments where ample parking would be paramount… [and] planned to remake parts of urban residential neighborhoods into suburban style residential sections” (Hurley 2016). Consequently, Interstates 20 and 75/80 (known as the Downtown Connector) were built through central Atlanta in the mid-1950s (Ambrose 2020). Large areas of mostly residential neighborhoods were demolished to accommodate these new roadways, as shown in Figure 8 below.

![Figure 8: Aerial Imagery of Area South of Downtown Atlanta, 1949 vs. Today (Source: Leonard 2018)](image-url)
Figure 9 and Figure 10 below show that many small commercial and industrial structures were removed in favor of homogenized land uses, parking lots and structures, and the widening of roads where walkable neighborhoods with diverse, human-scale development once existed.

Figure 9: The Widening of North Avenue in 1965 and North Avenue in 2015; Photo by Hurley (2016) and “Roads and Highways, View of Construction to Widen North Avenue, July 4, 1965” Atlanta Journal-Constitution Photograph from the Planning Atlanta Collection, Georgia State University Library (Source: Hurley 2016)

Figure 10: Pryor Street Before and After Kimball House was Replaced by A Block-Spanning Parking Deck (Source: Givens 2017)

These redevelopments led to drastic changes in the urban form of the City’s central business district and surrounding areas. Although the City of Atlanta appears to have returned to some forms of mixed-used development in more recent years, Hurley (2016) argues that these developments are overwhelmingly oriented towards accommodating the private automobile, and that much of the city’s land is still reserved for the transportation and storage of vehicles (i.e. roads and parking).
Like almost all major U.S. metropolitan areas, Atlanta’s suburban population growth has far outpaced core city expansion since the end of World War II. Per US Census data, the City of Atlanta added fewer than 90,000 residents between 1950 and 2010 despite expanding its land area by 2.5 times, while suburban Atlanta swelled by 4 million (Cox 2015). The growth of the urbanized area regionally over several decades is shown in Figure 11 below.

![Figure 11: Growth of the Atlanta Urbanized Area, 1950-2010 (Source: Atlanta Regional Commission 2021, 13)](image)

As a result, the Atlanta–Sandy Springs–Alpharetta Metropolitan Statistical Area (known as the Atlanta MSA, or informally as Metro Atlanta) expanded enormously, and is today sizably larger than the City of Atlanta. In 1970, the Atlanta MSA as defined by the federal government consisted
of only five counties (Cobb, Clayton, DeKalb, Fulton and Gwinnett), and spanned 1,731 square miles and had a population of 1,387,865 (Center for State and Local Finance, n.d.). As of 2019, the Atlanta MSA comprises 29 counties and spans 8,686 square miles with a population of over 6 million. It is also the ninth largest and one of the fastest-growing metro areas in the nation (Metro Atlanta Chamber, n.d.). The map of the Atlanta MSA today is shown in Figure 12 below.

![Map of the Atlanta-Sandy Springs-Roswell, GA MSA](image)

**Figure 12: Map of the Atlanta-Sandy Springs-Roswell, GA MSA (Source: Metro Atlanta Chamber, n.d.)**

Among large metro areas in the US (defined as having a population of over 1 million), Metro Atlanta was ranked as the most sprawling big metro area by a *Measuring Sprawl 2014* study.
conducted by the University of Utah’s Metropolitan Research Center (Smart Growth America 2014). In a 2016 report comparing US metropolitan areas, the Brookings Institution attributed Metro Atlanta’s sprawl to the peculiarities of land-use planning in the region, arguing that “…the regulatory framework for land use in metropolitan Atlanta undoubtedly contributes to its position at the top of many sprawl indices… Exclusionary zoning dominates the landscape, there is very little growth management, and urban containment is completely unknown. In many other metro areas where counties regulate development, their size allows them to make strategic decisions about preserving large amounts of land while allowing intensive development in other unincorporated areas… [however, this] does not appear to have been the recent pattern in Atlanta” (Brookings Institution 2016, 1).

The Metro Atlanta region is projected to keep growing over the next few decades, with total population and employment in the core 21-county area forecasted to increase by 51% (i.e. 2.9 million people) and 34% (i.e. 1.2 million jobs) respectively between 2015 and 2050. Growth forecasts for this period show that Metro Atlanta’s population will be distributed rather unevenly across the core counties, with some areas attaining much higher population densities than others (Atlanta Regional Commission, n.d.). The implications of these future projections have not gone unnoticed, especially in terms of transportation and commuting. The Atlanta Region’s Plan, prepared by the Atlanta Regional Commission (ARC) in its role as the federally designated Metropolitan Planning Organization (MPO), calls for investments of about $173 billion in federal, state and local funds to maintain and improve the region’s transportation infrastructure through 2050 (Atlanta Regional Commission 2021, 111). These funds are needed to keep the region moving, economically competitive and livable, and manage increasing demands on the region’s transportation system.
3.1.2 Commuting Trends

According to the *Measuring Sprawl 2014* report, people living in more sprawling metro areas have less options and higher costs transportation-wise, tend to walk and take transit less often, and tend to own more cars and spend more time driving (Smart Growth America 2014, 10). This particular finding certainly holds true for Metro Atlanta. As noted in the Atlanta Regional Commission’s Regional Transportation Plan document, “[Metro] Atlanta’s historic focus on highway investments and dispersed development is closely linked to current travel patterns and predominance of single-occupancy vehicle travel” (Atlanta Regional Commission 2021, 20). Per 2019 US Census data, an overwhelming 77% of commuters drive to work in Metro Atlanta (Donsky 2019). Mode share data for Atlanta commuters for 2008 through 2017, as shown in Figure 13, generally demonstrates that little has changed in over a decade.

![Figure 13: Metro Atlanta’s Changing Commuting Patterns, 2008-2017 (Source: Donsky 2019)](image-url)
The downside of driving en masse is that Atlanta is one of the most congested cities (ranked 10th worst in 2019) and also home to one of the most congested road corridors in the US (namely I-85/I-75, with a daily delay of 16 minutes), according to transportation analytics firm INRIX. Traffic congestion caused the average driver in Atlanta to lose 82 hours of time and $1,214 in 2019 (INRIX 2019). The effects of congestion are particularly pronounced during rush hour periods. For example, a study conducted by transportation app developer Drivemode on anonymized Android users’ GPS location data found that Atlanta drivers who take to the road between 4pm and 5pm spend more time in the car than commuters in almost every other big city – with New York City and Los Angeles as the only exceptions. The study also showed that for Atlanta drivers, commuting between 4pm and 5pm produced the longest commutes of the day, with the longest average commute being 52.91 minutes; however, drivers who left at 6pm instead of 4pm spent 15% less time in their cars. Interestingly, the length of morning commutes was found to vary by less than 5% regardless of departure time, suggesting that drivers can unfortunately expect consistent levels of congestion whether it is early or late in the morning peak period. In addition, GPS data showed that it took 2.3 minutes to drive a mere mile during Atlanta’s 8 to 9 a.m. morning rush hour, and that it took 2.5 minutes for the same distance during the 5 to 6 p.m. evening rush hour (Drivemode 2018).

Apart from traffic congestion issues, long commute times are also a bane of Atlanta-area commuters. A comparison of 2012-2016 American Community Survey data suggested that out of the 20 largest cities in the US, Atlanta drivers experience long car commute times more often than not (i.e. coming in at 4th worst with an average commute of 35 minutes, versus Washington D.C.’s worst average commute time of 41 minutes). Interestingly, the same data suggests that Atlanta public transit users fared no better, as Atlanta ranked second-worst with an average commute of
53 minutes versus Los Angeles’ worst average commute of 54 minutes for public transit commutes. Additional data revealed that 36% of Atlantans are able to make it to their destination in 30 minutes, 94% make it within an hour, and 6% make it in over an hour (Parker 2019).

As noted earlier, the Metro Atlanta region is projected to keep growing over future decades, with total population and employment in the core 21-county area forecasted to increase by 51% (i.e. 2.9 million people) and 34% (i.e. 1.2 million jobs) respectively between 2015 and 2050 (Atlanta Regional Commission, n.d.). Suffice it to say, the existing supply of road infrastructure in Metro Atlanta cannot support every one of these persons driving alone. Traffic congestion is already a serious problem in the Atlanta region, a statement agreed upon by 98% of respondents to the Georgia Commute Options’ 2019 Regional Commuter Survey. The same survey also found 1 in 3 commuters agreeing that their commute has become more difficult over the past years (Georgia Commute Options 2020, 4). Thus, investments in transportation including alternative commute modes, alongside improvements to the commuting experience, are arguably critical for maintaining regional growth in the coming decades.

3.1.3 Public Transit

Public transit services play a critical role in moving commuters around and helping to alleviate traffic congestion. However, public transit in Metro Atlanta has had a contentious history, with numerous setbacks inhibiting the growth of transit as detailed below.

3.1.3.1 Fixed Rail

Fixed-rail transit in Atlanta began with streetcars in the late 1800s, which enabled the existence of many of the City of Atlanta’s “intown neighborhoods” where residents could live beyond walking distance from downtown. Notably, the majority of Atlanta’s most densely
populated neighborhoods today are the neighborhoods once served by streetcars. Fixed-rail transit in Atlanta and across the United States rapidly declined after the 1920s, with the original streetcar system in the City of Atlanta ending in 1949 (Hurley 2015). Nonetheless, during the 1960s, Atlanta leaders began to campaign for a modern rapid transit system; in 1965, the Georgia General Assembly voted to approve the creation of the Metropolitan Atlanta Rapid Transit Authority (MARTA) in 1965 (Monroe 2012). In the following decades, however, suburban counties resisted the expansion of MARTA rail and bus lines into their jurisdictions, and rights-of-way for rail expansion in other areas proved extremely costly. MARTA, once envisioned as a cure for the City of Atlanta's dependence on automobile travel and its non-pedestrian orientation, did not end up fulfilling either goal (Ambrose 2020). As of 2017, a mere 8% of the Atlanta region’s core counties’ population lived within a mile of a rail station, down from 22% in 1970 (Freemark 2017).

Today, MARTA’s fixed-rail services involve over 338 rail cars servicing 38 rail stations along 48 miles of railroad tracks in Fulton and DeKalb counties, as shown in Figure 14 (Metropolitan Atlanta Rapid Transit Authority, n.d.). Of the 38 stations, 24 are in the City of Atlanta itself. Many rail stations within the City are designed as automobile-serving facilities, with customer parking, kiss-and-ride and bus driveways surrounding the main stations. MARTA also operates the Atlanta Streetcar, a 2.7-mile loop in and adjacent to Downtown Atlanta (Atlanta Department of City Planning, n.d., 12).
3.1.3.2 Buses

Other than fixed-rail lines, MARTA operates bus services almost exclusively in Fulton, DeKalb and Clayton counties. MARTA’s bus services involve 550 buses operating along 1,439 miles of roads on 101 routes (Metropolitan Atlanta Rapid Transit Authority, n.d.). Most of MARTA’s local bus routes provide service with headways of 20-30 minutes during peak hours in all parts of the City of Atlanta; as a rule, this service is concentrated on major corridors and in high-demand areas. All of MARTA’s bus lines feed into or intersect its rail lines to promote system connectivity (Atlanta Department of City Planning 2018, 8).

Other primary bus service providers in Metro Atlanta are CobbLinc, Gwinnett County Transit (GCT), and the Atlanta-Region Transit Link Authority (ATL). Both CobbLinc and GCT
provide local bus services within their respective counties (Cobb County and Gwinnett County) as well as commuter bus services to and from Downtown and Midtown Atlanta. The ATL operates 27 commuter bus routes (known as Xpress buses) that travel between designated park-and-ride facilities across 12 counties and locations in Downtown and Midtown Atlanta (Atlanta-Region Transit Link Authority, n.d.). Commuter bus routes are typically operated during select hours, namely morning and afternoon peak periods when commuters usually travel to and from work.

Overall, Figure 15 below depicts the routes for all primary transit service providers in Metro Atlanta. From Figure 15, it is clear that the further away one resides from the City of Atlanta’s downtown core, the less transit services there are available.

Figure 15: Primary Transit Networks in Metro Atlanta (Source: Freemark 2017)
3.1.4 TDM Efforts

There are no current TDM or trip reduction regulations for employers in the City of Atlanta or Metro Atlanta. Instead, there are a number of TDM employer programs, incentives, marketing and communications efforts initiated by Transportation Management Associations (TMAs) in certain City of Atlanta neighborhoods (Griffin 2019). The regional Georgia Commute Options program services 20 counties and provides customized worksite assistance, ride-matching services, and incentive programs to help employers and commuters plan better commutes (Georgia Commute Options n.d.). Since there are no regulatory requirements for employers, TDM providers and advocates are effectively attracting employer participation based entirely on the interest or willingness of employers.

3.1.5 Potential and Challenges for Alternative Commutes

The results of the Georgia Commute Options’ 2019 Regional Commuter Survey are of immediate relevance to this thesis topic, particularly where its revelations on Atlanta residents’ commuting habits as well as incentives and barriers to alternative mode use are concerned. In particular, the survey report highlighted the following findings (Georgia Commute Options 2020):

- When making a decision about mode choice, the ease of access to alternative modes is a critical factor that influences that decision. In core counties (i.e. Fulton, Dekalb, Cobb, Clayton, Gwinnett), more people walk or are picked up at home by a carpool/vanpool than drive alone to a park-and-ride lot or a bus/train station. However, for the non-core counties, most commuters drive alone to a park-and-ride lot or to a bus/train station;
For commuters who used alternative modes, the top motivating factors to do so were to save money (19%), to avoid congestion (14%), because no personal vehicle was available (14%), and for convenience (11%). Interestingly, more than half of survey respondents indicated that the greatest benefit from using an alternative mode was less stress/no traffic (55%) while saving money came in second (43%), although the latter was a top motivating factor for using an alternative mode;

Alternative mode commuters were also motivated by access to commute services, particularly those that reduce cost. Over four in ten respondents who used alternative modes had received at least one regional or local commute assistance service. The most common services cited in order of significance included a transit subsidy or discounted transit pass, help finding a carpool or vanpool partner, Guaranteed Ride Home, shuttle bus to a transit station/stop, or transit route or schedule information;

20 percent of commuters indicated that they could carpool or vanpool given their current work situation. At the time of the survey, about 5 percent of commuters either carpooled or vanpooled to work at least one day per week. However, of the two-thirds of commuters who said that they could not carpool or vanpool, under half stated that the compatibility of work schedules was the primary barrier;

The greatest barrier in the way of more transit use was the time it would take to commute. 60 percent of non-transit users, who already had access to transit and said they could use it, noted that they did not use transit because their commute trip would take too long. Other key barriers included difficulty getting to transit, incompatible transit schedules, and the distance from transit to home or work. Interestingly, the cost
of transit was a minor barrier, as only 8 percent of non-riders said that this deterred them from using transit to commute.

These findings suggest that there is some potential for commuters who drive alone to switch modes, more so if there is a perceivable benefit or reward. Survey respondents reported that a financial incentive would influence them to consider an alternative mode, such as a $5 per day incentive even if it ended after 30 days (nearly 50% of respondents), a monthly gas card for carpool members (over 40% of respondents), or a discounted monthly transit pass (34% of respondents) (Georgia Commute Options 2020, 9). However, it cannot be denied that major barriers exist for switching from driving to certain alternative modes. For carpooling, work schedule compatibility is the main issue; for transit, availability, accessibility, and trip length are key deterrents. In the Atlanta Regional Commission’s words, choosing how to travel to work is overwhelmingly shaped by the dependability of the travel mode (Atlanta Regional Commission 2020).

3.4 Background on the Employer

3.4.1 Corporate Headquarters (HQ) and Persons Assigned to the HQ

The employer for this case study is a large multinational corporation headquartered in Atlanta, GA. The corporate headquarters (hereafter referred to as the company HQ or simply the HQ) is located in Midtown Atlanta, with a mix of persons assigned to this location who are designated within the company as associates, contingent workers, or special affiliates. A person’s designation matters greatly as it determines the type of company badge that they receive, the type and extent of their information which is recorded in the company’s systems, and even the extent of the workplace benefits and initiatives that they are qualified to receive or participate in. This
includes commuter benefits, incentives and programs (Greenwald 2019, 60). Further details are summarized in Table 2.

**Table 2: Differences in Designations for Persons Assigned to the HQ**

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
</table>
| Associates      | • Direct employees of the company.  
                    • Receive company benefits (such as health insurance) and are eligible to receive financial incentives for company initiatives.  
                    • Allowed to use on-site workplace facilities such as the cafeteria, gym, and parking spaces.  
                    • Information is recorded in company’s HR systems.  
                    • Referred to as “associates” or “employees” in this report. |
| Contingent Worker| • Assigned to work with the company, but are often employed by a third party.  
                    • Do not receive company benefits, and are not eligible to receive financial incentives for company initiatives.  
                    • Allowed to use on-site workplace facilities such as the cafeteria, gym, and parking spaces. However, for certain paid facilities, fees charged may be higher compared to fees for associates.  
                    • Because they are not employed directly by the company, their personnel information records in the company’s HR systems may be incomplete or not up to date.  
                    • Referred to as “contingent workers”, “independent contractors”, or simply “contractors” in this report. |
| Special Affiliates| • All others who are not associates or contingent workers.  
                    • Includes company directors, retirees, and authorized company partners (who work with the company to produce goods and services, but are independent of the company).  
                    • Have access to the HQ for business and social purposes.  
                    • Are not expected to be on-site every day, and are in fact seldom on-site unless absolutely necessary.  
                    • For all intents and purposes, they are not considered as part of the HQ’s regular workforce.  
                    • Referred to as “special affiliates” in this report. |
Greenwald (2019, 61)’s study of ridesharing prospects for the HQ-based population reported an estimated total of 5,800 persons assigned to the HQ back then, of which 65% were associates and 35% were contingent workers; it is unclear if this number includes special affiliates. For the feasibility analysis outlined in Chapter 4, a more recent snapshot of the HQ-assigned population was obtained and analyzed.

3.4.2 Location of the HQ

The HQ is located in Midtown Atlanta, near the I-85/I-75 “Downtown Connector” that runs through the urbanized core of the City of Atlanta (see Figure 16 below). The HQ office campus consists of four main office buildings, three multi-level parking garages, several smaller ancillary buildings, and several surface parking lots. The HQ is located roughly ¾ of a mile away from the nearest MARTA rail station. It is also within walking distance of several MARTA bus stops located close by, and is about ¾ of a mile away from the nearest Xpress bus stop. There are docked bikeshare stations, albeit operated by third-party vendors, within walking distance.

Figure 16: General Location of Case Study Employer (Source: Greenwald 2019, 62)
As noted earlier, the HQ is frequented most of all by employees and contingent workers who have been assigned to work there. Special affiliates come to the HQ on an as-needed basis. The HQ is also open to employees and contingent workers from other worksites, who may be visiting the HQ for business (e.g. meetings) or for social purposes (e.g. lunch breaks).

Prior to the COVID-19 pandemic, there was no company-wide telework policy in place. However, reviews of daily badge-in records show that the pre-pandemic on-site population at the HQ tends to remain consistent from Mondays through Thursdays (around 3,800 persons), but drops to about half on Fridays. This suggests that many persons work from home on Fridays, or even work a compressed work schedule from Monday to Thursday and then take Friday off. This implies that there is some flexibility where the end of the workweek is concerned, although this may depend on the nature of the person’s work responsibilities and whether their manager approves of such flexible scheduling arrangements.

3.4.3 Commute Options Program at the HQ

The company’s HQ Workplace Experience department is responsible for optimizing and enhancing workplace experiences at the HQ, and managing the components that influence it. The general aim is to make the experience a positive one, and to facilitate a productive and pleasant time when the HQ’s services and amenities are used for work or non-work activities. The services and amenities in question are mostly on-site, inclusive of the cafeteria, health clinic, pharmacy, gym, wellness programs, lactation rooms for nursing mothers, dry cleaner, meeting spaces, office décor and equipment, and commuter facilities (e.g. parking spaces). However, some services are also effectively off-site, such as the commuting-related programs which effectively extend beyond the campus’ boundaries.
Under the HQ Workplace Experience department, the employee commutes experience – involving both HQ-centric facilities and program offerings – is managed by a dedicated team (hereafter referred to as the “commute options program team” or simply “HQ Commutes Team”). These initiatives are primarily driven by business-oriented decisions and the general objective of “making it easier for people to get to work.” That said, the HQ Commutes Team has significantly expanded its portfolio of commuter facilities and program offerings over time, to the point where it not only oversees the HQ’s parking assets but also offerings related to transit, active commuting, rideshare and so on. The justification given for this expansion is that the HQ Commutes Team, in line with the mission of the larger department, aims to provide a satisfying employee experience to all commuters and not just those who drive to work.

In addition, following the closure of several other Atlanta offices and the reassignment of their workers to the HQ in recent years (thus increasing the number of HQ-assigned workers and their vehicles), the HQ Commutes Team was called upon to monitor the parking situation at the HQ and help determine whether a parking crunch might be imminent. In fact, this issue has been a motivating factor to entice company personnel to adopt alternative commute modes, so as to lessen demand on HQ parking infrastructure.

The HQ Commutes Team’s major initiatives are explained below, as per the following categories: (i) Parking Management, (ii) Transit, (iii) Active Commuting, and (iv) Rideshare.

3.4.3.1 Parking Management

The employer directly owns and manages all the parking structures at the HQ, and daily parking is free for everyone. The policy of free parking was well-established in the company’s culture before the HQ Commutes Team was formed, and company leadership has made it clear that they will not be charging for parking anytime soon (Greenwald 2019, 63). As of early 2020,
there were a total of 4,235 parking spaces on campus which can be classified into the following categories (see Table 3):

<table>
<thead>
<tr>
<th>Area</th>
<th>Category</th>
<th>Total</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worker-Only (Non-Executive)</td>
<td>Regular</td>
<td>3,670</td>
<td>86.66</td>
</tr>
<tr>
<td></td>
<td>ADA</td>
<td>82</td>
<td>1.94</td>
</tr>
<tr>
<td></td>
<td>Carpool</td>
<td>29</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>Expectant Mothers</td>
<td>9</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>Electric Vehicles</td>
<td>86</td>
<td>2.03</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>17</td>
<td>0.40</td>
</tr>
<tr>
<td>Executive-Only (High-Level Associates / Employees)</td>
<td>Regular</td>
<td>172</td>
<td>4.06</td>
</tr>
<tr>
<td></td>
<td>ADA</td>
<td>3</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>Electric Vehicles</td>
<td>6</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>2</td>
<td>0.05</td>
</tr>
<tr>
<td>Guest Parking</td>
<td>Regular</td>
<td>150</td>
<td>3.54</td>
</tr>
<tr>
<td></td>
<td>ADA</td>
<td>7</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>Electric Vehicles</td>
<td>2</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td><strong>Total</strong></td>
<td><strong>4,235</strong></td>
<td><strong>100</strong></td>
</tr>
</tbody>
</table>

Parking spaces tagged as “ADA”, “Carpool”, “Expectant Mothers” or “Electric Vehicles” are considered “Premium Parking” as they are associated with unique uses. For example, ADA parking spaces can only be used by persons with disabilities who have placards or license plates indicating their status. Carpool, expectant mother and electric vehicle parking spaces are meant to work on a first come, first served, “honor system” basis, meaning that users are not supposed to park there unless they actually need to.

In terms of access to the parking spaces, each street-facing side of the corporate campus has a gated and guarded entrance for vehicles to pass through, en route to the nearest parking
garage or surface lot. For worker-only parking areas, entry and exit through the barrier gates is granted to all company affiliates as long as they have their company badges on hand. At the barrier gates, vehicle occupants are required to hand their badges to the guard on duty for badge scanning and identity verification, before the barrier gates are lifted.

Guests – who lack company badge(s) but usually arrive with their guest invitations on hand – must undergo a completely different process when they arrive at the HQ, if they arrive by vehicle and are looking for a place to park. They are directed to the dedicated guest parking area, which is separate from the worker-only and executive-only parking areas, and allowed entry and exit for that location once they show their guest invitation(s) to the guard on duty. Because they do not have company badges and park in an entirely different location, guest information is not recorded by the parking data system.

3.4.3.2 Parking Data

Parking-related data is produced by badge scans at the parking gates (except for the guest parking area). This data records the time and date of access, and the details of the person accessing the facility. The HQ Commutes Team has access to this data, and uses it to monitor parking usage trends and report on current and future levels of parking demand. One limitation of the parking data involves the fact that individual company badges, rather than vehicles, are scanned at the parking gates. Therefore, although it is possible to estimate the number of parking users at any given time (i.e. the number of persons who accessed the facility), this is not the same as the number of parking spaces being used at that point in time. It is entirely possible, after all, that a vehicle might have more than one occupant if the persons sharing the vehicle are carpooling together. In other words, there is a lack of comprehensive data on the true number of vehicles entering and
exiting the HQ’s parking facilities, not to mention the true number of vehicles with a single occupant versus multiple occupants (i.e. non-carpool versus carpool).

As noted previously, the HQ on-site population ebbs and flows from day to day, with Friday usually being the least populated workday. Correspondingly, parking numbers tend to drop on Fridays. People and vehicles come and go throughout the day, so the number of parking users in the HQ’s data system (which is recorded hourly) is always in flux. That said, in the months of late 2019 through early 2020, the HQ Commutes Team noted that the highest number of worker-only parking area users in a day was averaging around 80% and peaking at over 90% of worker-only parking spaces (assuming that no carpool vehicles were involved).

In general, the HQ Workplace Experience department’s goals concerning parking management at the HQ are to facilitate a positive employee experience while avoiding having to invest money into additional parking structures (Greenwald 2019, 65). Because of this, the high numbers of worker-only parking area users observed in late 2019 through early 2020 was flagged as a concern and a reason for renewing efforts to promote alternative commute modes.

3.4.3.3 Transit

Since the HQ is located somewhat near to transit facilities (i.e. the MARTA rail station, MARTA bus stops, and Xpress bus stops), using transit services to commute to and from the HQ is not an uncommon experience. The company’s arrangement with a dedicated commuter benefits vendor allows its employees located across North America – even those not assigned to the HQ – to conveniently purchase a monthly pass for transit services in their area ahead of time. The purchase order can be made with pre-tax dollars via the commuter benefits vendor’s platform, and the transit pass is delivered to the employee’s mailing address. The employee can choose to remain enrolled for the consecutive months so that the monthly pass is reloaded each month onwards, or
they can suspend enrolment at any time that they like. In addition, employees based in Georgia can also take advantage of a pre-tax subsidy towards their transit pass purchase each month. Most subsidy recipients are HQ-assigned employees, though there are others who are assigned to non-HQ work locations. Due to company prohibitions on financial benefits for contingent workers, no contingent worker can use the commuter benefits vendor’s platform to purchase monthly transit passes, or receive the pre-tax subsidy.

Based on past records, the number of HQ-assigned employees who were enrolled in the monthly transit pass and subsidy program from early 2019 through the end of February 2020 was around 200 persons on average each month.

3.4.3.4 Shuttle Bus

In addition, the HQ Workplace Experience department provides a dedicated shuttle bus service (hereafter referred to as the HQ Shuttle Bus) that plies a route connecting the HQ with several locations in Midtown/Downtown Atlanta, including the Civic Center MARTA rail station which is a major connecting point for Xpress bus routes. The HQ Shuttle Buses are free to ride, arrive approximately every 15 minutes, and pick up about 500 riders each day according to records for 2019 through the end of February 2020 (with the exception of Fridays, where ridership tends to drop due to the reduced on-campus population). HQ Shuttle Bus riders can be employees, contingent workers or even guests; riders must show either a company badge or guest invitation to the bus driver in order to board. That said, since badges and guest invitations are not scanned, there are no identifying details to determine the identities of riders or their precise pick-up and drop-off locations. The bus driver is tasked with recording the number of riders picked up or dropped off at every stop (via pressing a button on a software interface). However, this makes the
recording process subject to human error, and the numbers recorded are considered a rough estimate rather than a precise determination of HQ Shuttle Bus ridership.

3.4.3.5 Active Commuting

Any commuter who does not drive a personal vehicle to work but chooses to walk, bike or even scoot to the HQ is considered an active commuter. To accommodate their needs, there are several dedicated facilities at the HQ: a locker room with showers and reservable lockers, and a gated and covered bicycle parking area with a bicycle repair station and air pump on the side. HQ-assigned employees are also able to claim a small monthly financial incentive if they meet a minimum number of days for biking to/from work for that month; once again, this benefit is not available to contingent workers. From 2019 through the end of February 2020, an average of 14 individuals claimed this incentive each month. That said, occasional spot checks on occupancy levels in the bicycle parking area recorded anywhere from 2 to 30 bicycles parked at a time, although these numbers tended to fluctuate depending on the day’s weather (i.e. rainy and stormy days tend to mean less active commuters in general).

3.4.3.6 Rideshare

In early 2020, the Commutes Team was in the process of exploring new and improved partnerships with third-party vendors, primarily transportation network companies (TNCs), to provide rideshare benefits to HQ-assigned employees. A previous partnership had started in 2017 and ended in late 2019, which allowed HQ-assigned employees to book and use discounted shared rides with the designated TNC for trips to and/or from the HQ on weekdays. In 2018, this particular program resulted in a total of 13,500 shared rides, which can be interpreted as approximately 6,750 fewer vehicles on campus overall (Greenwald 2019, 66). Further analysis on the potential rideshare
market at HQ was conducted in early 2019 in the form of an employee survey; the findings are reported in Greenwald (2019). Based on the survey’s findings, the HQ Commutes Team set out to establish a new and improved rideshare program (combined with the appropriate technological / software platform) that would make it easier for HQ-assigned carpoolers to “match” with each other and share a ride, rather than involving external TNCs, drivers and/or passengers from outside the company. Discussions with potential vendors were underway as of early 2020.

3.4.4 Estimates of Commuting Population and Mode Share

Past estimates from previous years have suggested that over 90% of commuters use a personal vehicle to travel to and from work, although the context of these estimations is unknown. (Greenwald 2019, 67). As part of the feasibility analysis conducted for the employer, an updated analysis of mode share was performed using data from early March 2020 (i.e. prior to the COVID-19 pandemic and its effects). The findings are discussed in Chapter 5: Results.
CHAPTER 4: FEASIBILITY ANALYSIS

4.1 Rationale and Objectives

In recent years, the employer’s HQ Commutes Team conducted an internal review and determined that a critical, timely and fact-based analysis of the market for alternative commute services was very much needed. Two key questions were posed, namely (i) “What is the current ‘state of the commute’ for HQ-assigned workers?” and (ii) “What is the realistic likelihood that HQ-assigned workers who drive now will actually adopt alternative commute modes?” For the HQ Commutes Team, the answers to these questions would help to (i) provide insights about its current and potential users, and (ii) determine where to concentrate its efforts and what program offerings to prioritize, as opposed to offering a wide array of programs for a general audience.

In the past, insights on HQ-assigned workers’ commute behavior had been obtained from a variety of sources such as focus groups, user feedback on the HQ Commutes Team’s program offerings, and a survey aimed at assessing the potential and challenges for specific modes such as carpooling (i.e. in Greenwald (2019)’s study. To the best of the HQ Commutes Team’s knowledge, no in-depth analysis involving the entire HQ-assigned commuting population had been conducted thus far. Given this state of affairs, a feasibility analysis approach was developed as a joint effort between the HQ Commutes Team, company representatives, and Georgia Tech researchers.

For the feasibility analysis, the following primary objectives were established:

1) Understand where HQ-assigned workers live in (and perhaps even beyond) the Metro Atlanta region;

2) Assess how each HQ-assigned worker’s home location might influence or determine the alternative commute modes available to them; and
3) Assess the likelihood, given certain practical constraints, that HQ-assigned workers might be able to switch from driving to an alternative commute mode.

4.2 Methodology

The feasibility analysis process was initiated in 2020 and involved several adjustments before the final round of data collection and analysis was conducted in the first quarter of 2021. Though planning discussions for the feasibility analysis began in early 2020, the COVID-19 pandemic which erupted soon after gave rise to unprecedented challenges and forced a reset of plans. From March 2020 onwards, the HQ was closed in response to public health concerns, and the majority of workers were allowed to work from home. This created complications for the research process, the largest one being that real-time and on-site analyses or face-to-face interactions were now out of the question. Although a survey approach on workers and their future commuting plans was weighed as part of the feasibility analysis, the severity of COVID-19 and uncertainty over when the HQ would reopen led researchers to believe that this approach would be premature and ill-timed. In addition, in response to COVID-19, many Metro Atlanta transit providers suspended or dramatically altered their transit schedules, which led to issues in sourcing data that would reflect transit availability on ‘normal’ weekdays. Given these issues, it was crucial to establish a research process that could still meet original goals while adjusting for the uncertainties that COVID-19 had introduced. The final process involved the following steps, with methods that had been perfected after several trial runs:

1) Gathering data on HQ-assigned workers’ home locations;

2) Obtaining information on all available commute modes for each HQ-assigned worker, with certain parameters set to mimic real-life accessibility and availability constraints;
3) Evaluating the finalized travel times and distances for all commute modes available to each HQ-assigned worker, and in each case determining the one mode, out of all available commute modes, which would be “most competitive” with driving alone.

Further details for each step are elaborated upon in the following subsections.

4.2.1 Gathering data on HQ-assigned workers’ home locations

The feasibility analysis began with gathering data on HQ-assigned workers and their home locations, using the relevant company and vendor databases which the HQ Commutes Team had access to. A significant limitation to this approach involves the fact that contingent workers are not company employees, and thus unable to sign up for the benefits or financial incentives offered by the company (including those provided through third-party vendors). As such, information about contingent workers was generally missing from the databases that were consulted for this research. Because of this, contingent workers had to be excluded completely from the feasibility analysis due to a dearth of information. Similar issues affect the sub-population of HQ-assigned special affiliates, who are granted special access to the HQ but otherwise do not appear in the company’s databases which were consulted for this research. While this creates an inherent flaw with the analysis, this issue was unavoidable and the only recourse was to make a note of it.

As of March 2021, the total HQ-assigned population comprised 5,569 persons, inclusive of employees, contingent workers and special affiliates. Two separate databases were consulted, the first being Database A which comprises the most recent roster of HQ-assigned employees. This roster is updated in the first week of every month. For this feasibility analysis, a copy of the March 2021 roster was obtained, totaling 3,226 HQ-based employees (i.e. 58% of the total HQ-assigned population). The second database, known as Database B, contains a roster of physical mailing addresses for all employees who had signed up for specific company benefits inclusive of
commuter benefits. The information in Database A was matched with the information in Database B to obtain the mailing addresses for HQ-assigned employees as of March 2021. Since Database A and Database B were not linked directly, but managed by different entities, this necessitated using a common key in the form of employees’ email addresses to verify that a person in Database A was the same person in Database B. Roster files were downloaded in Microsoft Excel format (.xlsx files). Scripts written in the R programming language were used to access the files, rename data columns, and match data entries from separate roster files on the basis of the common key. Additional data cleaning was performed to validate the results of the matching exercise.

For the next step, the resulting dataset was examined for any data anomalies. The following types of anomalies were noted and then removed from the dataset, as their inclusion would have been of no use to this research:

a) 68 employees for whom no address data was available at all;

b) 2 employees who had used the HQ’s address as their mailing address; and

c) 20 employees who had used a P.O. Box address as their mailing address.

After these anomalies were removed, a final dataset consisting of 3,136 HQ-based employees and their mailing addresses was obtained. This represents 97% out of the original total of 3,226 HQ-based employees, and 56% out of the total population of 5,569 HQ-assigned persons in March 2021. For the purpose of this research, it is assumed that the employees’ mailing addresses are the same as their home addresses (i.e. that they choose to receive their mail where they live).

4.2.2 Obtaining information on all available commute modes for each HQ-assigned worker, with certain parameters set to mimic real-life accessibility and availability constraints

For this part of the process, it was assumed that the types of commute mode choices available to HQ-assigned employees for trips from their home locations to the HQ can be broken
down into several categories, as per Table 4 and Table 5. “Single mode” trips, as detailed in Table 4, are trips that involve no transfers between modes and no transfer points along the way. “Multimodal” trips, as detailed in Table 5, involve transfers between modes (e.g. walking to a transit stop, and boarding a transit vehicle to the next stop) and transfer points such as transit stops or park-and-ride facilities.

Table 4: Types of “Single Mode” Mode Choices Available to HQ-Assigned Employees

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Drive</td>
<td>Commuter drives a personal vehicle from their home to the HQ (and parks their personal vehicle there).</td>
</tr>
<tr>
<td>2</td>
<td>Bike</td>
<td>Commuter cycles from their home to the HQ (and parks their bicycle there).</td>
</tr>
<tr>
<td>3</td>
<td>Walk</td>
<td>Commuter walks from their home to the HQ.</td>
</tr>
</tbody>
</table>

Table 5: Types of “Multimodal” Mode Choices Available to HQ-Assigned Employees

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| 4   | Walk + Nearest Transit + Walk (*) | i) Commuter walks from their home to the nearest transit stop (no further than ¾ of a mile in walking distance). This transit stop may be a bus stop or a MARTA rail station.  
ii) Commuter boards a transit vehicle (bus / rail). They may need to transfer to another transit vehicle along the way, depending on the trip.  
iii) Commuter reaches the final transit stop of their trip.  
iv) Commuter walks from the final transit stop to the HQ. |
| 5   | Drive + Express / Commuter Bus + Walk | i) Commuter drives a personal vehicle from their home to the nearest express/commuter Bus park-and-ride facility (and parks their personal vehicle there).  
ii) Commuter boards an express/commuter Bus vehicle. They may need to transfer to another transit vehicle along the way, depending on the trip.  
iii) Commuter reaches the final transit stop of their trip.  
iv) Commuter walks from the final transit stop to the HQ. |
Table 5 Continued

<table>
<thead>
<tr>
<th>Mode Choice</th>
<th>Description</th>
</tr>
</thead>
</table>
| 6 Drive + MARTA Rail + Walk | i) Commuter drives a personal vehicle from their home to the nearest MARTA rail station (and parks their personal vehicle there).  
ii) Commuter boards a rail vehicle. They may need to transfer to another rail vehicle along the way, depending on the trip.  
iii) Commuter reaches the final rail station of their trip.  
iv) Commuter walks from the final rail station to the HQ. |
| 7 Bike + MARTA Rail + Bike | i) Commuter cycles from their home to the nearest MARTA rail station.  
ii) Commuter boards a rail vehicle (and brings their bicycle with them). They may need to transfer to another rail vehicle along the way, depending on the trip.  
iii) Commuter reaches the final rail station of their trip.  
iv) Commuter cycles from the final rail station to the HQ (and parks their bicycle there). |
| 8 Walk + MARTA Rail + Walk (*) | i) Commuter walks from their home to the nearest MARTA rail station (no further than 1 ½ mile in walking distance).  
ii) Commuter boards a rail vehicle. They may need to transfer to another rail vehicle along the way, depending on the trip.  
iii) Commuter reaches the final rail station of their trip.  
iv) Commuter walks from the final rail station to the HQ. |

(*) It is entirely possible that for some workers, using either mode choice #4 or #8 ends up with the same trip as an option, in cases where the “nearest transit stop (no further than ¾ of a mile in walking distance) is effectively the “nearest MARTA rail station” as well. However, there are many other cases where the “nearest transit stop” is not the “nearest MARTA rail station”, but say a standalone MARTA bus stop instead, which means that either mode choice would result in completely different trips. In addition, the methodologies used to determine trip availability for mode choice #4 and #8 are entirely different (as detailed in later sections). For these reasons, mode choice #4 and #8 are in distinct categories of their own.

The following sections detail the methodologies used to acquire information on possible trip routes, travel times, travel distances and so on associated with each mode choice.
4.2.2.1 “Single Mode” Mode Choices

For all “single mode” mode choices, Google Distance Matrix API was the chosen trip planner tool for assessing availability, accessibility, travel times and distances for trips involving said mode. This API essentially “is a service that provides travel distance and time for [origins and destinations… it] returns information based on the recommended route between start and end points, as calculated by the Google Maps API, and consists of rows containing duration and distance values” (Google, n.d.) Although there is usually more than one viable route for any given origin and destination pair, the API’s final route recommendation is often the one that is fastest in terms of travel time, and as far as possible, also shortest in terms of distance. Though other APIs exist for public use, Google Distance Matrix API was ultimately chosen due to its ease of use and general affordability (including free trial credits to perform multiple API requests over a span of 90 days). In addition, Google Maps is one of the most popular trip planning and navigational tools for travelers today, so it is likely that many commuters in Metro Atlanta, inclusive of HQ-based employees, already or would likely use Google Maps for commute activities.

The process of obtaining travel time and distance results from Google Distance Matrix API involved running Python scripts to execute several consecutive tasks, in this order:

i) The Python script references the dataset containing the details of the 3,136 HQ-based employees and their addresses;

ii) For each dataset entry, the Python script extracts the address of the employee in question so that it can be used as a search parameter for the API request;

iii) Using a Google API key (linked to a Google email account), the Python script sends out an API request with the employee’s address as the trip’s “origin” and the HQ’s
address as the trip’s “destination”, along with other customized search parameters depending on the type of travel mode being queried;

iv) The returned output for each API request is returned in JSON format and is read by the Python script; the script then extracts the relevant details and writes them to an Excel spreadsheet for easy reading;

v) After the last step is successfully completed, the Python script moves on to the next entry in the dataset and repeats the entire process. This procedure allows for multiple automated queries to be made.

For each type of travel mode that was queried, the API requests had to be formatted carefully to match the specifications listed in the Google Distance Matrix API documentation for developers (Google, n.d.). Details are provided in subsequent sections.

a) Drive

For driving-based API requests, the following search parameters were applied in each request: mode, origins, destinations, departure_time, and traffic_model. Table 6 below notes the meanings of these parameters and the input supplied for each. A sample of the full Python code used for such an API request is provided in Appendix A.
Table 6: Search Parameters and Details for “Drive” Mode Choice using Google Distance Matrix API

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter</th>
<th>Meaning (Source: Google, n.d.)</th>
<th>Input</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>mode</td>
<td>Specifies the mode of transport to use when calculating distance.</td>
<td>“driving”</td>
</tr>
<tr>
<td>2</td>
<td>origins</td>
<td>The starting point for calculating travel distance and time. One or more locations may be supplied, separated by the pipe character (</td>
<td>), in the form of a place ID, an address, or latitude/longitude coordinates.</td>
</tr>
<tr>
<td>3</td>
<td>destinations</td>
<td>One or more locations to use as the finishing point for calculating travel distance and time.</td>
<td>Company HQ’s address</td>
</tr>
</tbody>
</table>
| 4   | departure_time | For requests where the travel mode is driving: departure_time can be specified to receive a route and trip duration (response field: duration_in_traffic) that take traffic conditions into account. departure_time has to be specified as an integer in seconds since midnight, January 1, 1970 UTC. It must be set to the current time or some time in the future; it cannot be in the past. | One of several possibilities (in UTC timestamp format):  
  • 1621944000 (Tuesday, May 25, 2021 at 8:00am)  
  • 1621942200 (Tuesday, May 25, 2021 at 7:30am)  
  • 1621940400 (Tuesday, May 25, 2021 at 7:00am)  
  • 1621924200 (Tuesday, May 25, 2021 at 6:30am) |
| 5   | traffic_model | Specifies the assumptions to use when calculating time in traffic. This setting affects the value returned in the duration_in_traffic field in the response, which contains the predicted time in traffic based on historical averages. The traffic_model parameter may only be specified for requests where the travel mode is driving, and where the request includes a departure_time. | “pessimistic” |

The optional departure_time and traffic_model parameters involved some unique circumstances which had to be adjusted for, as follows:
(i) **departure_time**

It was important to use this parameter or the choice of route and duration would be based on average time-independent traffic conditions (Google, n.d.).

The research assumes that workers will want to arrive at the HQ by 8:30am on a weekday to begin work, and closer to 8:30am rather than earlier; ideally, an “arrival time” of 8:30am would have been specified for this API query. However, Google Distance Matrix API does not allow an “arrival time” parameter to be set for a driving-based API request. Since only a “departure time” parameter can be set, it follows that the inputted departure time should be earlier than 8:30am, so that the worker can arrive at the HQ no later than 8:30am – but not so early that it causes the worker to have ample idling time at the HQ before the 8:30am mark.

Therefore, one workaround was to run the API query multiple times with different departure_time inputs tested, and to see if the worker’s arrival time at the HQ exceeds 8:30am or not. Based on the results, the final departure_time input chosen for each dataset entry was the one that provided the worker with the arrival time before and closest to 8:30am.

(ii) **traffic_model**

There are three available values for this parameter, which are: (i) “best_guess” (default), which indicates that the returned duration_in_traffic should be the best estimate of travel time given what is known about historical traffic conditions and live traffic (which becomes more important the closer the departure_time is to now); (ii) “pessimistic”, which indicates that the returned duration_in_traffic should be longer than the actual travel time on most days, though occasional days with particularly bad traffic conditions may exceed this value; and (iii) “optimistic”, which indicates that the returned duration_in_traffic should be shorter than the actual
travel time on most days, though occasional days with particularly good traffic conditions may be faster than this value (Google, n.d.).

In selecting the input to use, a more “pessimistic” scenario is assumed to better reflect traffic conditions in Metro Atlanta prior to COVID-19, namely in ‘normal’ times and not during outlier events. The reason for this is because the COVID-19 pandemic had a significant effect in terms of reducing traffic volumes and congestion, as many workers avoided their workplaces and switched to working from home. Because of this, the Google Maps algorithm was modified in the later part of 2020 to only consider the most recent weeks of travel and traffic patterns at the time that a query is made (Haselton 2020). At the time of this research, traffic volumes and congestion had not fully returned to pre-COVID-19 levels (TomTom, Inc., n.d.). Thus, if the “best guess” or “optimistic” values were to be used, the traffic model would only take into account recent traffic history rather than reflecting Metro Atlanta traffic conditions on an average day prior to COVID-19. To compensate for these issues, the “pessimistic” setting was used instead.

For driving-based API requests, the Python script was configured to retrieve the following results in JSON format and write them to an Excel spreadsheet for easy reading:

- distance of the entire trip (in miles);
- duration of the entire trip (in minutes), which represents the length of the trip in free-flow speed or essentially uncongested conditions; and
- duration_in_traffic of the entire trip (in minutes), which represents the length of the trip when the traffic_model parameter representing traffic congestion is used.

b) Bike

For biking-based API requests, the following search parameters were applied in each request: mode, origins, and destinations. In terms of the mode parameter, “bicycling” was inputted
to request distance calculation for bicycling via bicycle paths and preferred streets (where available) (Google, n.d.). As for the origins and destinations parameters, the same input that had been supplied for driving-based API requests was used, i.e. the employee’s home address and the HQ’s address respectively.

Notably, for biking-based API requests, departure_time and arrival_time parameters are not required. This is because Google Maps assumes a standard moving speed of roughly 10 mph irrespective of the length of a cyclist’s journey, or the time of day (and the amount of traffic congestion at the time) (Chandler 2021). As such, attempting to provide input with regards to departure_time or arrival_time has no effect on the results.

For biking-based API requests, the Python script was configured to retrieve the following results in JSON format and write them to an Excel spreadsheet for easy reading:

- distance of the entire trip (in miles); and
- duration of the entire trip (in minutes).

c) Walk

For walking-based API requests, the following search parameters were applied in each request: mode, origins, and destinations. In terms of the mode parameter, “walking” was the input supplied to request distance calculation for walking via pedestrian paths and sidewalks (where available) (Google, n.d.). As for the origins and destinations parameters, the same input for driving-based and biking-based API requests was used, i.e. the employee’s home address and the HQ’s address respectively.

Similar to biking-based API requests, departure_time and arrival_time parameters are not required for walking-based API requests. This is because Google Maps assumes a standard moving speed of roughly 3 mph irrespective of the length of a pedestrian’s journey, or the time of day (and
thus the amount of traffic congestion at the time), or whether the pedestrian is using a road or a footpath (Graehl 2021). As such, attempting to provide input with regards to departure_time or arrival_time has no effect on the results.

For walking-based API requests, the Python script was configured to retrieve the following results in JSON format and write them to an Excel spreadsheet for easy reading:

- distance of the entire trip (in miles); and
- duration of the entire trip (in minutes).

4.2.2.2 “Multimodal” Mode Choices

Ideally, the same set of tools would have been used to derive travel times, distances, and trip plans for all commute modes assessed throughout this research. Although Google Distance Matrix API worked well for trip planning involving “single-mode” mode choices (as per the previous section), initial experiments with using it for “multimodal” mode choices” resulted in failure or blank results. The reason for this failure is very much due to the COVID-19 pandemic and its impacts on transportation in 2020 and 2021. As it turns out, Google Maps and its APIs are set up to use the most recent transit schedules (which use the General Transit Feed Specification or GTFS format) that have been released by public transit authorities. Each time a transit schedule is updated by its provider, the Google Maps API defaults to using it in place of the previous one. Since this research was conducted in 2020 and 2021, during which the COVID-19 pandemic was ongoing, many transit providers in the United States had scaled down their transit services dramatically or altered their schedules, including the primary transit providers in Metro Atlanta (Goldbaum and Wright 2020). Because of this, attempts to use Google Distance Matrix API resulted in blank results for many dataset entries, simply because transit services were not available in particular areas of Metro Atlanta at that point in time. However, for all intents and purposes,
this research assumes that transit services will be eventually restored to their pre-pandemic levels once the COVID-19 pandemic has subsided. Because of this, GTFS files representing transit services in pre-pandemic times were sourced and used to simulate what ‘normal’ transit services – and not COVID-19 era services – would be like.

Primary transit providers in the Metro Atlanta region are MARTA, CobbLinc, Gwinnett County Transit (GCT), and Xpress. The latest GTFS file for MARTA can be found on its website (https://www.itsmarta.com/app-developer-resources.aspx) while GTFS files for the other three providers can be found on the Atlanta Regional Commission’s Open Data Portal (https://hub.arcgis.com/datasets/GARC::regional-gtfs-feeds/about). In addition, archives of past GTFS files for MARTA and Xpress are hosted on Transit Feeds, which is an open online archive of official public transport data (http://transitfeeds.com/). However, since GTFS feeds are usually updated with every new version, this necessitated making a decision about which GTFS files to use based on several key factors. These factors include: (i) the period of time that the GTFS file in question is/was valid for, (ii) the date of the transit trip that is being queried, and (iii) any unique circumstances that may have affected the version of the GTFS file that is being used (i.e. how a particular GTFS file compares to previous versions).

For MARTA, it was clear that the GTFS file covering the period of March 30, 2020 to May 8, 2020 (released on March 26, 2020) represented MARTA’s transit services immediately before the COVID-19 pandemic forced changes upon its services and schedules. As such, this GTFS file was chosen and Tuesday, March 31, 2020 was the date chosen for querying transit trips. From there, searches were made for GTFS files from the other three providers which would effectively cover the Tuesday, March 31, 2020 date as well. In the end, the following GTFS files were downloaded for use (see Table 7 below):
Table 7: GTFS Files Downloaded for Use in the Feasibility Analysis

<table>
<thead>
<tr>
<th>No.</th>
<th>Transit Provider</th>
<th>Period of Validity (i.e. values for feed_start_date and feed_end_date in the GTFS feed_info.txt file)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MARTA</td>
<td>March 30, 2020 to May 8, 2020</td>
</tr>
<tr>
<td>2</td>
<td>CobbLinc</td>
<td>September 6, 2020 to June 26, 2021*</td>
</tr>
<tr>
<td>3</td>
<td>Gwinnett County Transit</td>
<td>March 24, 2020 to January 1, 2021</td>
</tr>
<tr>
<td>4</td>
<td>Xpress</td>
<td>December 15, 2019 to March 15, 2020*</td>
</tr>
</tbody>
</table>

In the process of downloading and examining these files, two issues were encountered which involved CobbLinc and Xpress GTFS files. For CobbLinc, the only GTFS file publicly available was for the period of September 6, 2020 to June 26, 2021, implying that it had likely been released during the COVID-19 pandemic and not before. While using a GTFS file from during the COVID-19 pandemic was not optimal, there were no other options in this case. In addition, an examination of CobbLinc’s service alerts suggested that CobbLinc had not cut any geographical coverage during the pandemic but instead had consolidated some routes albeit with slightly modified schedules (Cobb County Georgia, n.d.). In other words, the CobbLinc GTFS file on hand could still be used despite some flaws. As for Xpress, the archived GTFS file on hand showed a validity period of December 15, 2019 to March 15, 2020, which stops short of the test date of Tuesday, March 31, 2020. However, the next available Xpress GTFS file showed a release date of 5 January 2021 which would have been unsuitable for pre-COVID-19 schedule purposes. Because of this, the Xpress GTFS file with the validity period of December 15, 2019 to March 15, 2020 was chosen and modifications were made to the GTFS’s file’s feed_info.txt file to “extend” its validity to cover the Tuesday, March 31, 2020 test date. Since Xpress had operated relatively fixed routes and schedules pre-pandemic, it was assumed that the chosen file would still adequately represent Xpress even if it were “off” by two weeks in reality.
Since GTFS files come in .txt format and would be tedious to read manually, it was necessary to locate a software tool that can read and process GTFS information quickly, and also act as a trip planner and recommender in a similar fashion to the Google Distance Matrix API. The tool chosen for this purpose was OpenTripPlanner 1.5 (hereafter referred to as OTP). OTP is described as “an open-source and cross-platform multi-modal route planner written in Java. It uses imported OpenStreetMap (OSM) data for routing on the street and path network and supports multi-agency public transport routing through imported General Transit Feed Specification (GTFS) feeds” (Young 2021). OTP is also described as “receiving support from public agencies, startups, and transportation consultancies alike… [and powering] regional and national journey planning services around the world, as well as several popular multi-city mobile applications” (OpenTripPlanner: Multimodal Trip Planning, n.d.). For walking portions of transit-based trips, OTP assumes a walk speed of 3 miles per hour, like Google Distance Matrix API (Open Trip Planner API, n.d.). OTP in theory can also be used to suggest driving-based trips, although one major limitation is that it is an offline tool and therefore unable to provide trip recommendations and information based on historical levels of traffic congestion, unlike Google Distance Matrix API. Therefore, for this research, OTP was chosen as a tool primarily for planning transit-based trips. OTP was also chosen for its customizability, since it can be configured to work with any GTFS file regardless of release date provided that the contents within the GTFS file are valid.

Since OTP is an open-source tool which is constantly undergoing improvements and updates introduced by developers and contributors, newer versions are released from time to time. At the time of writing, the most recent version of OTP was OTP 2.0 (albeit a beta version). However, initial attempts to use OTP 2.0 resulted in several errors and blank results, and a search of OTP forum discussions suggested that these issues were due to a bug that might be fixed in later
OTP releases (GitHub 2020). Given the time-sensitive nature of this research, OTP 1.5 (i.e. the previous version and a more stable release of OTP instead) was used instead.

That said, one major limitation with OTP 1.5 is that it currently works with a single pair of origin and destination locations, but does not allow the user to indicate that they want to make a stopover at a specific location mid-way through the trip. However, the feasibility analysis approach for several of the “multimodal” mode choices requires that the commuter make transfers at specific transfer points, e.g. at a Park-and-Ride facility for the “Drive + Express/Commuter Bus + Walk” mode choice, or a MARTA rail station for mode choices which involve driving, biking or walking to a MARTA rail station and boarding a MARTA rail vehicle there. The workarounds for these limitations are discussed in subsequent sections which are specific to the affected mode choices.

Similar to the process for extracting trip information from Google Distance Matrix API, queries for all 3,136 HQ-based employees in the dataset had to be made to OTP to obtain trip recommendations and trip information for each employee. For this purpose, R scripts were written to make multiple automated queries, like the Python scripts used earlier for the Google Distance Matrix API. A key R package used was “otpr” created by OTP contributor Marcus Young, which was set up precisely to help OTP users submit a query to the relevant OTP API resource, parse the OTP response and return useful R objects (Young 2021). The returned output for each OTP request was returned to the R console and was read by the R script. The script then extracted the relevant details and wrote them to an Excel spreadsheet for easy reading, before moving on to the next entry in the dataset and repeating the entire process.

Per the instructions in the “otpr” package’s user manual, the OTP requests had to be formatted carefully so that the inputs for the required search parameters would make sense and return the desired results (Young 2021). Details are provided in the subsequent sections.
a) Walk + Nearest Transit + Walk

For this type of API request, the following search parameters were applied in each request: *mode*, *fromPlace*, *toPlace*, *date*, *time*, *arriveBy*, *maxWalkDistance*, *minTransferTime*, *maxItineraries*, *detail*, and *includeLegs*. Table 8 notes the meanings of these parameters and the input supplied for each. A sample of the full R code used for such an API request is provided in Appendix B.

Table 8: Search Parameters and Details for “Walk + Nearest Transit + Walk” Mode Choice using Google Distance Matrix API

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter</th>
<th>Meaning (Source: Young 2021)</th>
<th>Input</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>mode</td>
<td>Specifies the mode of transport to use when calculating distance. TRANSIT will use all available transit modes. Default is CAR. WALK mode is automatically added for TRANSIT, BUS, RAIL, TRAM, and SUBWAY.</td>
<td>“TRANSIT”</td>
</tr>
<tr>
<td>2</td>
<td>fromPlace</td>
<td>The origin of the trip.</td>
<td>Employee’s home address (in latitude/longitude coordinates)</td>
</tr>
<tr>
<td>3</td>
<td>toPlace</td>
<td>The destination of the trip.</td>
<td>Company HQ’s address (in latitude/longitude coordinates)</td>
</tr>
<tr>
<td>4</td>
<td>date</td>
<td>The desired date of travel, in the format mm-dd-yyyy. Only relevant for transit modes. Default is the current system date.</td>
<td>&quot;03-31-2020&quot; (Tuesday, March 31, 2020 test date)</td>
</tr>
<tr>
<td>5</td>
<td>time</td>
<td>If arriveBy is FALSE (the default) this is the desired departure time, otherwise the desired arrival time. Must be in the format hh:mm:ss. Only relevant for transit modes. Default is the current system time.</td>
<td>“08:30:00” (8:30 am)</td>
</tr>
<tr>
<td>6</td>
<td>arriveBy</td>
<td>Whether a trip should depart (FALSE) or arrive (TRUE) at the specified date and time. Default is FALSE.</td>
<td>“TRUE”</td>
</tr>
</tbody>
</table>
The optional *maxWalkDistance* and *minTransferTime* parameters involved some unique circumstances which had to be adjusted for, as follows:

(i) **maxWalkDistance**

The distance between the HQ and the MARTA rail station closest to the HQ is around ¾ of a mile. It follows that if a HQ-based worker is willing to walk the last-mile distance of ¾ of a mile from that MARTA rail station to the HQ, they should also be willing to walk the same first-mile distance from their home location to the nearest transit stop. For these reasons, the parameter was set at 1207.01 meters which is equal to ¾ of a mile.
(ii) \textit{minTransferTime}

In general, MARTA bus vehicles have a reported headway of 20 minutes during peak hour service (Atlanta Department of City Planning, n.d., 8). It is assumed that if a worker has to wait more than 20 minutes to make a transfer between transit vehicles, they will not be interested in this transit option. For this reason, this parameter was set at 1200 seconds which is equal to 20 minutes. Overall, for this type of API request, the R script was configured to retrieve 3 detailed itineraries as R objects and write them to an Excel spreadsheet for easy reading. Each itinerary contained the following objects:

- \textit{start} i.e. the start time of the entire trip;
- \textit{end} i.e. the end time of the entire trip;
- \textit{duration} i.e. the duration of the entire trip (in minutes);
- \textit{walkTime} i.e. the total time spent on walking, within the entire trip (in minutes);
- \textit{transitTime} i.e. the total time spent on transit, within the entire trip (in minutes);
- \textit{transfers} i.e. the number of transfers within the entire trip;
- \textit{legs}, of which there might be more than one, with each leg containing its own objects:
  (i) \textit{mode} i.e. the mode of the leg;
  (ii) \textit{departureWait} i.e. the time spent on waiting before the departure time (usually most applicable to trips involving transit vehicles);
  (iii) \textit{duration} i.e. the duration of the leg (in minutes);
  (iv) \textit{distance} i.e. the distance of the leg (in meters);
  (v) \textit{routeShortName} i.e. the name of the route (usually most applicable to trips involving transit vehicles);
  (vi) \textit{fromName} i.e. the name of the departure point;
(vii) \textit{fromLon} i.e. the longitude of the departure point;

(viii) \textit{fromLat} i.e. the latitude of the departure point;

(ix) \textit{toName} i.e. the name of the arrival point;

(x) \textit{toLon} i.e. the longitude of the arrival point; and

(xi) \textit{toLat} i.e. the latitude of the arrival point.

One limitation of OTP is that even with the aforementioned parameters set, it may recommend trips that are hypothetically possible whether or not the trips make sense in term of timing, time commitments, or convenience. For example, out of the 3 trip recommendations provided by OTP for a particular case, there may be a trip that starts at 5:30am or takes multiple transfers to reach the destination by transit (i.e. showing that this particular transit trip is quite inconvenient for the worker in question). Because of this, further work had to be done to filter out “unreasonable” transit trips which HQ-based workers would likely be reluctant to attempt. Thus, the following filters and conditions were imposed on the R results that had been written to Excel:

i) Departure time of no earlier than 6:00am on Tuesday, March 31, 2020;

ii) Only one transfer between transit vehicles allowed (e.g. a trip coded as “WALK-BUS-WALK-SUBWAY-WALK”, meaning that the worker in question walks to the nearest bus stop, takes the bus to a MARTA rail station, walks to the rail station platform, takes the MARTA rail to the MARTA rail station closest to the HQ, and walks to the HQ). It is assumed that such a transit trip is still doable for workers; however, anything more such as having to take two buses to reach a MARTA rail station to board a rail vehicle would be a turn-off;

iii) For walking transfers (not inclusive of first-mile and last-mile legs of the trip), no more than a \(\frac{1}{4}\) mile (or 402.335 meters) distance between one transit stop and the
The assumption is that transfers between successive transit vehicles should not be inconvenient and require more walking to the point that the commuter has to leave the immediate area. The ¼ mile distance limit is expected to act as a catchment radius to fulfil this condition.

Since OTP was set up to provide 3 recommendations, this allowed for more filtering to be done so as to ensure that even if the first recommendation did not fulfil all the above criteria, the second and third recommendations could be tried as backup options. If all three recommendations did not fulfil the criteria given, the “Walk + Nearest Transit + Walk” mode choice was effectively eliminated as an option for the worker in question. Of the remaining trip recommendations which did fulfil the criteria, the one with the shortest travel time was chosen as the final recommendation.

b) Drive + Express/Commuter Bus + Walk

At the time of this research, a total of 35 Park-and-Ride facilities in Metro Atlanta were in operation as transit stops for express/commuter buses. The commuter bus routes in question are operated by MARTA, CobbLinc, and Xpress. However, the Hickory Grove Park-and-Ride facility (which is under Xpress’ purview) was not in operation then and had no routes traveling to/from it, so it was excluded from the analysis (Atlanta-Region Transit Link Authority 2021).

As noted earlier, one limitation of OTP is that it is not set up to handle trips where the user indicates that they want to make a stopover at a specific location mid-way through the trip. Since this particular mode choice requires a transfer at a Park-and-Ride facility, and a driving trip beforehand to reach the facility, this complicates the process of trip planning using OTP alone. Because of this, a mix of steps and tools had to be used (see Table 9).
Table 9: Steps and Tools for Determining Trip Recommendations, Travel Times and Travel Distances for the “Drive + Express/Commuter Bus + Walk” Mode Choice

<table>
<thead>
<tr>
<th>No.</th>
<th>Step</th>
<th>Tool</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>For each active Park-and-Ride facility, determine which employees live within 30 minutes’ driving distance.</td>
<td>OTP API</td>
</tr>
<tr>
<td>2</td>
<td>Obtain preliminary travel times and distances for the “Drive” leg(s) of the trip(s) from each employee’s home to the Park-and-Ride facility.</td>
<td>Google Distance Matrix API</td>
</tr>
<tr>
<td>3</td>
<td>For each employee, select the two nearest Park-and-Ride facilities in terms of “Drive” travel distances.</td>
<td>Microsoft Excel</td>
</tr>
<tr>
<td>4</td>
<td>Obtain trip recommendations and travel times for transit trips from said selected Park-and-Ride facilities.</td>
<td>OTP API</td>
</tr>
<tr>
<td>5</td>
<td>Obtain final travel times and distances for the “Drive” leg(s) of the trip(s) from each employee’s home to the selected Park-and-Ride facility.</td>
<td>Google Distance Matrix API</td>
</tr>
<tr>
<td>6</td>
<td>Add all legs together from steps (4) and (5) and sum up total travel times and distances for each Park-and-Ride facility option.</td>
<td>Microsoft Excel</td>
</tr>
<tr>
<td>7</td>
<td>Choose the final Park-and-Ride facility option for each employee, based on the shortest travel time.</td>
<td>-</td>
</tr>
</tbody>
</table>

The process involved for each step listed in Table 9 is detailed below:

(i) For each active Park-and-Ride facility, determine which employees live within 30 minutes’ driving distance

For this step, OTP was configured via R script to produce travel time isochrones (which are essentially catchment maps) to determine how far a worker might be able to travel by car within a 30-minute time limit. The following parameters and inputs were used: toPlace and fromPlace (both using the latitude and longitude coordinates of every Park-and-Ride facility active in Metro Atlanta at the time), mode (with “CAR” as the input), and cutoffSec (with “1800” or 1800 seconds as the input, equivalent to the 30-minute time limit), as instructed in Marcus Young’s OTP tutorial (Young 2021, 5). With these settings, the R script was executed and OTP returned the isochrone
map polygons for each active Park-and-Ride facility in the form of zipped shapefiles, which were imported into ESRI ArcGIS software. ArcGIS was used to overlay each Park-and-Ride facility’s travel time isochrone on a map of all HQ-based employee address locations, to identify the employees who live within a 30-minute driving distance.

(ii) Obtain preliminary travel times and distances for the “Drive” leg(s) of the trip(s) from each employee’s home to the Park-and-Ride facility

Based on the results in Step 1 – namely a list of employees and their home addresses within a 30-minute driving distance for every active Park-and-Ride facility – travel times and distances for a “Drive” trip from each employee’s home location to the Park-and-Ride facility in question were obtained. Google Distance Matrix API, accessed by Python scripts, was used to facilitate this process. However, the duration_in_traffic parameter was not applied, and the departure_time parameter was inconsequential as the aim was to obtain values for travel times and distances regardless of traffic conditions.

(iii) For each employee, select the two nearest Park-and-Ride facilities in terms of “Drive” travel distances

In this step, the available choices of Park-and-Ride facilities for each employee were narrowed down to the two facilities nearest to employees’ homes in terms of travel distances. The reason for narrowing down to two facilities rather than one is because of the chance that an employee’s home location is equidistant to more than one Park-and-Ride facility on the map, even if in reality one facility is located closer to Midtown Atlanta (the ultimate destination) while another is further away. Selecting the nearest two locations was a preliminary step in the filtering process to narrow down a final recommendation.

(iv) Obtain trip recommendations and travel times for transit trips from said Park-and-Ride facilities
The procedure for this step largely follows the procedure outlined for the “Walk + Nearest Transit (Bus / MARTA Rail) + Walk” mode choice. That is, OTP was used to obtain trip recommendations and travel times, albeit with the fromPlace parameter supplied with the latitude and longitude coordinates of the Park-and-Ride facility in question as the input. Of all the trip recommendations, the one with the shortest travel time was chosen as the final recommendation.

(v) Obtain final travel times and distances for the “Drive” leg(s) of the trip(s) from each employee’s home location to the selected Park-and-Ride facility

This step mimics step (2), albeit with altered conditions. For each employee, only the nearest two Park-and-Ride facilities were used as destinations to obtain travel times and distances. The duration_in_traffic parameter was applied with “pessimistic” as the input. For departure_time parameter, the inputted value was derived by taking the value of the departure time for the transit leg of the trip (i.e. when the worker boards the express/commuter bus) and counting backwards by 30 minutes. This is a rough estimate that assumes the worker in question needs around 30 minutes maximum to arrive to the Park-and-Ride facility. The results of this API query were recorded as the finalized estimates of travel times and distances for the “Drive” leg(s) of the trip(s).

(vi) Add all legs together from steps (4) and (5) and sum up total travel times and distances for each Park-and-Ride facility option

The purpose of this step was to obtain a finalized travel time and distance for each Park-and-Ride facility option for each worker, by adding up the travel times and distances for separate legs of the entire journey (i.e. essentially divided into “Drive from home to the Park-and-Ride facility” and “Board an express/commuter bus to Midtown Atlanta or as close as possible to the HQ, and walk the rest of the way there”).

(vii) Choose the final Park-and-Ride facility option for each employee, based on the shortest travel time
The purpose of this step was to determine the final Park-and-Ride facility (and the express/commuter bus) that the worker would most likely use for their overall trip. Among the two options for each worker, the one with the overall shortest travel time was chosen.

c) **Drive + MARTA Rail + Walk**

At the time of this research, a total of 38 MARTA rail stations were in use. However, for this research, the MARTA rail station nearest to the HQ was excluded (as an origin point for rail trips going to the HQ), while other MARTA rail stations were retained for analysis. Like the “Drive + Xpress Bus + Walk” mode choice, a mix of steps and tools had to be used as per Table 10.

**Table 10: Steps and Tools for Determining Trip Recommendations, Travel Times and Travel Distances for the “Drive + MARTA Rail + Walk” Mode Choice**

<table>
<thead>
<tr>
<th>No.</th>
<th>Step</th>
<th>Tool</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>For each employee, determine the two nearest MARTA stations.</td>
<td>Google Places API (Nearby Search)</td>
</tr>
<tr>
<td>2</td>
<td>Obtain trip recommendations and travel times for transit trips from</td>
<td>OTP API</td>
</tr>
<tr>
<td></td>
<td>said selected MARTA rail stations to the HQ.</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Obtain final travel times and distances for the “Drive” leg(s) of the trip(s) from each employee’s home location to the selected MARTA rail station.</td>
<td>Google Distance Matrix API</td>
</tr>
<tr>
<td>4</td>
<td>Add all legs together from steps (2) and (3) and sum up total travel times and distances for each MARTA rail station option.</td>
<td>Microsoft Excel</td>
</tr>
<tr>
<td>5</td>
<td>Choose the final MARTA rail station option for each employee, based on the shortest travel time.</td>
<td>-</td>
</tr>
</tbody>
</table>

The process involved for each step listed in Table 10 is detailed below:

**(i) For each employee, determine the two nearest MARTA stations**

Google Places API’s “Nearby Search” function was deployed for this purpose, since this API is designed to search for places within a specified area (Google, n.d.). Key search parameters
included rankby and type; the respective inputs used were “distance” and “subway_station.” For every dataset entry, the first two results returned by the Python script were recorded in an Excel spreadsheet.

(ii) Obtain trip recommendations and travel times for transit trips from said selected MARTA rail stations to the HQ

For this step, using OTP to obtain trip recommendations and travel times, the fromPlace parameter was supplied with the latitude and longitude coordinates of the MARTA rail station in question as the input. From the obtained trip recommendations, the one with the shortest travel time was chosen as the final trip recommendation.

(iii) Obtain final travel times and distances for the “Drive” leg(s) of the trip(s) from each employee’s home location to the selected MARTA rail station

This step was performed for each of the two MARTA rail stations identified as being nearest to each employee’s home address. The duration_in_traffic parameter was applied, with “pessimistic” as the input. For the departure_time parameter, the value used as the input was derived by taking the value of the departure time for the transit leg of the trip (i.e. the time that the worker begins their transit trip via MARTA rail) and counting backwards by 30 minutes. This is a rough estimate that assumes the worker in question needs around 30 minutes at maximum to arrive to the MARTA rail station. The results of this API query was recorded as the finalized estimates of travel times and distances for the “Drive” leg(s) of the trip(s).

(iv) Add all legs together from steps (2) and (3) and sum up total travel times and distances for each MARTA rail station option

The purpose of this step was to obtain a finalized travel time and distance for each MARTA rail station option for each worker, by adding up the travel times and distances for
separate legs of the entire journey (i.e. essentially divided into “Drive from home to the MARTA rail station” and “Board a MARTA rail vehicle to Downtown Atlanta or as close as possible to the HQ, and walk the rest of the way there”).

(v) **Choose the final MARTA rail station option for each employee, based on the shortest travel time**

The purpose of this step was to determine the final MARTA rail station facility (and MARTA rail route) that the worker would most likely use for their overall trip. Among the two options for each worker, the one with the overall shortest travel time was chosen.

d) **Bike + MARTA Rail + Bike**

Similar to the process for the “Drive + MARTA Rail + Walk” mode choice, a mix of steps and tools were used as per Table 11.

**Table 11: Steps and Tools for Determining Trip Recommendations, Travel Times and Travel Distances for the “Bike + MARTA Rail + Bike” Mode Choice**

<table>
<thead>
<tr>
<th>No.</th>
<th>Step</th>
<th>Tool</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>For each employee, determine the two nearest MARTA stations.</td>
<td>Google Places API (Nearby Search)</td>
</tr>
<tr>
<td>2</td>
<td>Obtain trip recommendations and travel times for transit trips from said selected MARTA rail stations to the HQ.</td>
<td>OTP API</td>
</tr>
<tr>
<td>3</td>
<td>Obtain final travel times and distances for the “Bike” leg(s) of the trip(s) from each employee’s home location to the selected MARTA rail station.</td>
<td>Google Distance Matrix API</td>
</tr>
<tr>
<td>4</td>
<td>Add all legs together from steps (2) and (3) and sum up total travel times and distances for each MARTA rail station option.</td>
<td>Microsoft Excel</td>
</tr>
<tr>
<td>5</td>
<td>Substitute the last-mile “Walk” leg’s travel time with an estimate for “Bike” instead.</td>
<td>Google Distance Matrix API</td>
</tr>
<tr>
<td>6</td>
<td>Choose the final MARTA rail station option for each employee, based on the shortest travel time.</td>
<td>-</td>
</tr>
</tbody>
</table>
Since the process in Table 11 is nearly identical to the process for “Drive + MARTA Rail + Walk”, it need not be elaborated extensively here. However, some minor changes performed involved steps (3) and (5). As previously noted, this mode choice assumes that the worker will bike to the MARTA rail station, bring their bike with them on board the train, and after reaching their final transit stop they will bike to the HQ. Because of this, the travel time estimate of the “Walk” leg of the transit trip that is produced by OTP had to be replaced by a travel time estimate for “Bike” instead. As noted before, travel time estimates for “Bike” journeys calculated by Google Distance Matrix API are consistent regardless of departure time.

From the obtained trip recommendations, the one with the shortest travel time was chosen as the final trip recommendation.

e) Walk + MARTA Rail + Walk

Similar to the prior two mode choices, a mix of steps and tools were used as per Table 12.

Table 12: Steps and Tools for Determining Trip Recommendations, Travel Times and Travel Distances for the “Walk + MARTA Rail + Walk” Mode Choice

<table>
<thead>
<tr>
<th>No.</th>
<th>Step</th>
<th>Tool</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>For each employee, determine the two nearest MARTA stations.</td>
<td>Google Places API (Nearby Search)</td>
</tr>
<tr>
<td>2</td>
<td>Obtain trip recommendations and travel times for transit trips from said selected MARTA rail stations to the HQ.</td>
<td>OTP API</td>
</tr>
<tr>
<td>3</td>
<td>Obtain final travel times and distances for the “Walk” leg(s) of the trip(s) from each employee’s home location to the selected MARTA rail station.</td>
<td>Google Distance Matrix API</td>
</tr>
<tr>
<td>4</td>
<td>Add all legs together from steps (2) and (3) and sum up total travel times and distances for each MARTA rail station option.</td>
<td>Microsoft Excel</td>
</tr>
<tr>
<td>5</td>
<td>Choose the final MARTA rail station option for each employee, based on the shortest travel time.</td>
<td>-</td>
</tr>
</tbody>
</table>
Since the process in Table 12 is near identical to the process for “Drive + MARTA Rail + Walk” and “Bike + MARTA Rail + Bike”, it need not be elaborated extensively here. From the obtained trip recommendations, the one with the shortest travel time was chosen as the final trip recommendation.

4.2.3 Evaluating the finalized travel times and distances for all commute modes available to each HQ-assigned worker, and in each case determining the one mode, out of all available commute modes, which would be “most competitive” with driving alone.

Once all available mode choice options were explored for each employee, and the trip recommendations as well as travel details were obtained for each, the results for each available alternative mode for each worker were evaluated and compared. Further details of this process, as well as the results of this exercise, are discussed in the following chapter.
CHAPTER 5: RESULTS

The results of the feasibility analysis are presented in this chapter, beginning with a discussion of employees’ home locations and their distance from the HQ. For each mode choice that was explored in the feasibility analysis, the following aspects are discussed: (i) the number of employees identified as potential commuters for that mode, (ii) travel distances from said potential commuters’ home locations to the HQ, (iii) travel times from said potential commuters’ home locations to the HQ, (iv) a comparison of travel time for the mode in question versus driving in traffic congestion, and (v) a map showing the home locations of said potential commuters for the mode in question. After the results for all modes have been elaborated on, a comparison is made between all alternative mode choices versus driving in traffic congestion, and the results of an exercise in selecting the “best” alternative mode for each employee is discussed. The employer’s HQ mode share versus the potential alternative commuting market is also noted, and last but not least the caveats of the feasibility analysis are explained.

5.1 Employees’ Home Locations

Figure 17 shows the approximate home locations of 3,136 HQ-assigned employees, assuming that their mailing addresses in the dataset are equivalent to their home addresses. For employees who live unusually far away from the HQ, one reason for this might be that they are remote workers who do not need to come to the HQ on a daily basis. Another possibility is that these employees have since relocated closer to the HQ, but neglected to update their mailing / home addresses in the employer’s database. However, there is no way to tell if either guess is accurate, since the current data sources do not provide these insights.
Figure 17: Map of all HQ-Assigned Employees’ Home Locations

Figure 18 provides a close-up look of the Metro Atlanta region and the employees whose home locations are in the area. The majority of employees (3,034 persons or 97%) live within the 29-county Metro Atlanta region. A total of 637 persons (20%) live within the City of Atlanta (outlined in blue), while 2,397 persons (76%) live outside of the City of Atlanta’s borders but within the 29-county region still. A remaining 102 persons (3%) live outside the Metro Atlanta region entirely, some within the State of Georgia and others outside of it.
Figure 18: Map of the Metro Atlanta Region and HQ-Assigned Employees in the Area
5.2 Feasibility of Mode Choices

The following sections explore the results for each of the commute mode choices tested in this feasibility analysis, namely: (i) Drive, (ii) Bike, (iii) Walk, (iv) “Walk + Nearest Transit + Walk”, (v) “Drive + Express/Commuter Bus + Walk”, (vi) “Drive + MARTA Rail + Walk”, (vii) “Bike + MARTA Rail + Bike”, and (viii) “Walk + MARTA Rail + Walk”.

5.2.1 Drive

5.2.1.1 Employees Identified as Potential Driving Commuters

The feasibility analysis assumes that all HQ-assigned employees have access to a personal vehicle, and that driving from home to work is the default commute mode choice. As such, driving-based travel distances and times are calculated for all employees.

5.2.1.2 Driving Distances from Home Locations to the HQ

Here, the distance from an employee’s home location to the HQ is measured in terms of miles of driving distance (as derived from Google Distance Matrix API’s request results) rather than a straight-line (“as the crow flies”) distance. At first glance, the shortest distance in the entire dataset was determined to be under a mile, while the longest distance was an astonishing 2,449 miles (courtesy of an employee located at the opposite end of the country).

As shown in Table 13, when grouped into 5-mile bins, the majority of employees (81%) are shown to live within 0-30 driving miles of the HQ. 15% live within 30-45 driving miles of the HQ, and 2% live between 45 and 120 driving miles of the HQ. The remaining 2% (78 persons) live more than 120 miles of driving distance from the HQ – which works out to at least 2 hours of driving time in free-flow or uncongested traffic conditions.
Table 13: Number of Employees According to Driving Distance from Home to HQ

<table>
<thead>
<tr>
<th>Miles</th>
<th>HQ-Assigned Employees</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>%</td>
</tr>
<tr>
<td>0 to 5</td>
<td>405</td>
<td>12.91%</td>
</tr>
<tr>
<td>5+ to 10</td>
<td>432</td>
<td>13.78%</td>
</tr>
<tr>
<td>10+ to 15</td>
<td>408</td>
<td>13.01%</td>
</tr>
<tr>
<td>15+ to 20</td>
<td>417</td>
<td>13.30%</td>
</tr>
<tr>
<td>20+ to 25</td>
<td>437</td>
<td>13.93%</td>
</tr>
<tr>
<td>25+ to 30</td>
<td>427</td>
<td>13.62%</td>
</tr>
<tr>
<td>30+ to 35</td>
<td>250</td>
<td>7.97%</td>
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<tr>
<td>35+ to 40</td>
<td>135</td>
<td>4.30%</td>
</tr>
<tr>
<td>40+ to 45</td>
<td>72</td>
<td>2.30%</td>
</tr>
<tr>
<td>45+ to 50</td>
<td>29</td>
<td>0.92%</td>
</tr>
<tr>
<td>50+ to 55</td>
<td>12</td>
<td>0.38%</td>
</tr>
<tr>
<td>55+ to 60</td>
<td>10</td>
<td>0.32%</td>
</tr>
<tr>
<td>60+ to 65</td>
<td>6</td>
<td>0.19%</td>
</tr>
<tr>
<td>65+ to 70</td>
<td>1</td>
<td>0.03%</td>
</tr>
<tr>
<td>70+ to 75</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>75+ to 80</td>
<td>1</td>
<td>0.03%</td>
</tr>
<tr>
<td>80+ to 85</td>
<td>7</td>
<td>0.22%</td>
</tr>
<tr>
<td>85+ to 90</td>
<td>2</td>
<td>0.06%</td>
</tr>
<tr>
<td>90+ to 95</td>
<td>2</td>
<td>0.06%</td>
</tr>
<tr>
<td>95+ to 100</td>
<td>2</td>
<td>0.06%</td>
</tr>
<tr>
<td>100 to 105</td>
<td>1</td>
<td>0.03%</td>
</tr>
<tr>
<td>105+ to 110</td>
<td>1</td>
<td>0.03%</td>
</tr>
<tr>
<td>110+ to 115</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>115+ to 120</td>
<td>1</td>
<td>0.03%</td>
</tr>
<tr>
<td>120+</td>
<td>78</td>
<td>2.49%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>3,136</strong></td>
<td><strong>100.00%</strong></td>
</tr>
</tbody>
</table>
Figure 19, which is a histogram created in Microsoft Excel, shows the distribution of values for driving distances from employees’ home locations to the HQ; values of over 120 miles are excluded for ease of viewing. As the distance between home and the HQ grows, the number of employees tapers off.

![Figure 19: Employees’ Driving Distances, 0 to 120 Miles](image)

Figure 20 shows the distribution of values for driving distances of 0 to 120 miles from employees’ home locations to the HQ, as a boxplot graph created in Microsoft Excel. The graph is divided into four sections, including a rectangle (“box”) that is split into two parts and thin T-shaped projections on each end (“whiskers”). The boxplot (and others like it in later sections of this chapter) shows the 25th, 50th, and 75th percentiles of values with points beyond the whiskers as outliers. Outliers follow the Tukey industry standard of 1.5 times the length of the box (known
as the interquartile range). The mean is denoted by the “X” marker in the chart and represents the average of all the data points, or 20 miles. The median is denoted by the midline of the box, and is 19 miles (Microsoft 365 Blog 2015).

Figure 20: Employees’ Driving Distances, 0 to 120 Miles (Boxplot)

Figure 21 is a map of the HQ-assigned employees who live up to 120 miles away in terms of driving distance. The redder the shade of the map point, the further away the employee. In this map, the employee furthest away from the HQ is located exactly 120 miles away in another state.
Figure 21: Map of Employees According to Driving Distance, 0 to 120 Miles
5.2.1.3 Driving Travel Times from Home Locations to the HQ

Figure 22 shows the distribution of driving times from home to HQ in free-flow or uncongested traffic conditions, obtained via the *duration* value returned from Google Distance Matrix API requests. Figure 23, on the other hand, shows the distribution of driving times from home to HQ in congested traffic conditions. These driving times are obtained via the *duration_in_traffic* value, which is returned when the “pessimistic” traffic model parameter is applied to simulate the effects of morning peak-hour traffic congestion on driving times. For ease of viewing, the numbers shown in Figure 22 and Figure 23 are only for the employees who live within a driving distance of 120 miles. Unsurprisingly, the resulting distribution of driving times in Figure 23 skews higher compared to Figure 22.

![Figure 22: Driving Times in Uncongested Traffic, 0 to 120 Miles](image)
Figure 23: Driving Times in Traffic Congestion, 0 to 120 Miles

Figure 24 below provides another point of reference, in the form of a boxplot graph comparing the results of Figure 22 with Figure 23. Per Figure 24, the median value for driving in uncongested conditions is 27 minutes, while the median value for driving in traffic congestion is 36 minutes (i.e. with the “pessimistic” traffic model parameter applied).
Figure 24: Driving Times in Uncongested Traffic vs. in Traffic Congestion, 0 to 120 Miles

Figure 25 shows where employees live and is color-coded according to the amount of driving time that traffic congestion adds to their driving commute. At first glance, there appears to be a correlation between driving distance from home to HQ and the amount of additional travel time when traffic congestion is in effect. For employees who live nearer to the HQ, the overall amount of time that they spend in traffic may be short enough so that they are not excessively
delayed by traffic congestion. That said, there may be specific roads, routes or areas of the region which are prone to traffic congestion no matter what.

Figure 25: Map of Employees According to Additional Travel Time for Driving in Traffic Congestion vs. Driving in Uncongested Traffic, 0 to 120 Miles
5.2.2 Bike

5.2.2.1 Employees Identified as Potential Biking Commuters

Although Google Distance Matrix API readily provides travel estimates for biking to work for all employees in the dataset, time and distance constraints do not make this a viable choice for everyone. Notably, the National Household Travel Survey (2009)’s survey of bicycling trips to and from work found that the average trip length was 3.8 miles and the average travel time was 21.2 minutes (Kuzmyak and Dill 2012, 10). Meanwhile, the US Department of Transportation’s A Guidance Manual for Implementing Effective Employer-based Travel Demand Management Programs suggests that short-distance commutes of five miles or less favor bicycling as a mode choice (U.S. Department of Transportation 1993, 13-14). Google Distance Matrix API also assumes an average bicycling speed of 10 mph which amounts to around 30 minutes of travel time for 5 mph of biking distance. Therefore, a limit of 5 miles was chosen as a cut-off distance to narrow down the number of employees who would be more likely to bike. Some employees may choose to bike longer distances, but it is assumed that these are biking enthusiasts who are not new to commuting via bike and would not need to be enticed by incentives to bike.

Figure 26 shows the distribution of employees within a 5-mile biking distance of the HQ. A total of 408 employees meet this criteria, or 13% of all HQ-assigned employees.
Figure 26: Employees Identified as Potential Biking Commuters
5.2.2.2 Biking Distances from Home Locations to the HQ

Figure 27 shows the distribution of values for the additional miles of travel distance that a biking trip adds to an employee’s commute versus a driving trip, derived for each of the 408 potential biking commuters. The values shown in Figure 27 are obtained by taking the total miles of each employee’s biking distance and subtracting the total miles of their driving distance from the former. If biking distances are larger than driving distances, this results in positive values and vice versa. Figure 27 shows that for many potential biking commuters, biking would result in the same or even less distance travelled versus driving, presumably because they might bike about the same route that they previously drove. There are a handful of potential biking commuters for whom biking distance would be several miles shorter than driving distance (resulting in negative values in Figure 27). This may be due to off-road shortcuts which can be taken for biking trips. There are also some employees who would see their commute distance increase if they switch from driving to biking (i.e. 82 out of 408 employees or 20%), though by no more than 1.2 miles at most.

![Figure 27: Additional Travel Distance for Biking vs. Driving](image)

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That said, one caveat of these findings is that Google Maps API’s trip recommendations are often based on the shortest path possible for biking. However, research on biking behavior has shown that cyclists may not take the shortest path possible, but may go out of their way to ride on facilities with bike infrastructure and on low traffic streets. In choosing a biking route, less experienced bicyclists will place higher importance on factors that make the trip easier – namely routes with less traffic and requiring less physical effort (Dill and Gliebe 2008).

5.2.2.3 Biking Travel Times from Home Locations to the HQ

Figure 28 shows the distribution of values for the additional travel time that a biking trip adds to an employee’s commute versus a driving trip in non-congested conditions, for all potential biking commuters. The values in Figure 28 are obtained by taking the total minutes of each employee’s biking travel time and subtracting the total minutes of their driving time (in non-congested conditions) from the former. If one’s biking travel time is longer than non-congested driving travel time, this results in positive values and vice versa. In the same vein, Figure 29 shows the distribution of values for the additional travel time that a biking trip adds on to an employee’s commute versus a driving trip in congested conditions. Both figures show that biking adds travel time to a person’s commute if they had been driving before, which is not surprising since biking is slower than driving on average. However, if traffic congestion is present (which increases driving time), the difference in travel time for biking versus driving is lessened (i.e. when Figure 28 and Figure 29 are compared).
Figure 28: Additional Travel Time for Biking vs. Driving in Uncongested Traffic

Figure 29: Additional Travel Time for Biking vs. Driving in Traffic Congestion
That said, operating on the assumption that employees must leave home to reach the HQ by 8:30am, the morning peak-hour would definitely be in effect during this time. Therefore, it is more appropriate to compare biking with driving in congested conditions, rather than uncongested conditions. Figure 30 thus shows the range of travel times for biking versus driving in congested conditions. The median value for biking is 21 minutes while the median value for driving in congested conditions is 15 minutes.

![Box plot showing travel times for biking vs driving in traffic congestion]

**Figure 30: Travel Time for Biking vs. Driving in Traffic Congestion**

Figure 31 shows where potential biking commuters live and is color-coded according to the amount of travel time that is added to their commute, if they bike instead of drive in traffic congestion. In general, the further away one lives from the HQ, the greater the travel time added to one’s commute if one chooses to bike instead of drive. However, according to the map, biking adds no more than 20 minutes at most to one’s commute.
Out of all 408 employees, the longest biking commute possible would take 35 minutes to cover 5 miles, versus 23 minutes of driving in traffic congestion. The increase in travel time may
take some getting used to, but the health and exercise benefits provided by biking to commuters may help to make up for the increase in travel time.

5.2.3 Walk

5.2.3.1 Employees Identified as Potential Walking Commuters

Similar to biking, Google Distance Matrix API provides travel estimates for walking to work for all employees in the dataset. However, time and distance constraints do not make this a viable choice for everyone. Notably, the National Household Travel Survey (2009)’s survey of walking trips to and from work found that the average trip length was one mile and the average travel time was 16.2 minutes (Kuzmyak and Dill 2012, 10). Meanwhile, the US Department of Transportation’s A Guidance Manual for Implementing Effective Employer-based Travel Demand Management Programs suggests that short-distance commutes of two miles or less favor walking as a mode choice (U.S. Department of Transportation 1993, 13-14). However, with Google Distance Matrix API’s assumed walking speed of 3 mph, a mile of walking would take 20 minutes while two miles of walking would take 40 minutes. Therefore, a 1.5 mile distance (which works out to about 30 minutes of walking) was chosen as a cut-off distance to narrow down the number of employees who would be more likely to walk to work.

Figure 32 below shows the distribution of HQ-assigned employees who live within a 1.5 mile walking distance of the HQ. In total, there are a total of 41 persons who live within 1.5 miles of the HQ, comprising 1% of the total HQ-assigned employee population.
5.2.3.2 Walking Distances from Home Locations to the HQ

Figure 33 shows the distribution of values for the additional miles of travel distance that a walking trip adds to an employee’s commute versus a driving trip, derived for each of the 41
potential walking commuters. The resulting variations in travel distance are so slight as to be insignificant. This is likely because these employees’ commute routes are very short to begin with and they would effectively walk the same route that they drove previously.

![Figure 33: Additional Travel Distance for Walking vs. Driving](image)

5.2.3.3 Walking Travel Time from Home Locations to the HQ

Figure 34 shows the distribution of values for the additional travel time that a walking trip adds to an employee’s commute versus a driving trip in non-congested conditions, calculated for each of the 41 employees in question. In the same vein, Figure 35 shows the distribution of values for the additional travel time that a walking trip adds to an employee’s commute versus a driving trip in congested conditions. Here, the impacts are significant. Walking clearly adds more time to a person’s commute as opposed to driving, which is not surprising since walking is much slower. Interestingly, even if traffic congestion is present, the difference in travel time for walking versus driving is near-identical to when there is no congestion (i.e. when the results in Figure 34 and
Figure 35 are compared). Traffic congestion has little impact presumably because the distance travelled is short, i.e. no more than 1.5 miles.

![Figure 34: Additional Travel Time for Walking vs. Driving in Uncongested Traffic](image1)

![Figure 35: Additional Travel Time for Walking vs. Driving in Traffic Congestion](image2)
Figure 36 shows the range of travel times for walking versus driving in congested traffic conditions (which are assumed to be in effect if employees leave home during the morning peak-hour with the aim of reaching the HQ by 8:30am). The median value for walking is 30 minutes, and the median value for driving in congested conditions is 9 minutes.

Figure 37 shows where potential walking commuters live and is color-coded according to the amount of travel time that is added to their commute, if they walk instead of driving in traffic congestion. As expected, the further away one lives from the HQ, the greater the amount of time that is added to one’s commute if one chooses to walk instead of drive.
Out of all 41 employees, the longest walking commute would take 32 minutes for 1.5 miles, which would otherwise take about 10 minutes of driving in congested conditions. The threefold
increase in travel time may be challenging for some, but the health and exercise benefits provided by walking to commuters may help to make up for the increase in travel time.

5.2.4  *Walk + Nearest Transit + Walk*

5.2.4.1 *Employees Identified as Potential “Walk + Nearest Transit + Walk” Commuters*

As noted in Chapter 4, the “Nearest Transit” label indicates that the employee walks no more than ¾ of a mile from their home to the nearest transit stop (i.e. a bus stop or a MARTA rail station), to board a bus / rail vehicle (which is not an express/commuter bus). OTP 1.5 was used to provide a maximum of three trip recommendations per employee, which were filtered to ensure that the finalized trip recommendation would be reasonable. The criteria for filtering was:

(i)  Departure time of no earlier than 6:00am on Tuesday, March 31, 2020;

(ii) Only one transfer between transit vehicles allowed;

(iii) For walking transfers (not inclusive of first-mile and last-mile legs of the trip), no more than a ¼ mile distance between one transit stop and the next.

Table 14 shows the effects of this filtering on the number of potential transit commuters.

<table>
<thead>
<tr>
<th>Step #1</th>
<th>Employees with OTP-Provided Transit-Based Trip Recommendations</th>
<th>Employees with No Transit-Based Trip Recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>%</td>
</tr>
<tr>
<td>Pre-Filtering</td>
<td>1,124</td>
<td>35.84</td>
</tr>
<tr>
<td>Post-Filtering</td>
<td>958</td>
<td>30.56</td>
</tr>
</tbody>
</table>

^ OTP failed to find any trip recommendations at all for these employees.

* Inclusive of 7 walk-only trips, which OTP recommended, but which were discarded as they do not involve any transit vehicles per se.
A pool of 958 persons (31% of all employees) was left after the initial filtering process. The home locations of the employees in this initial pool are shown in Figure 38.

**Figure 38:** Initial Pool of Employees Identified as Potential “Walk + Nearest Transit + Walk” Commuters
However, a sanity check performed on the trip data for this initial pool suggested that many of the 958 commuters would find this mode choice rather unworkable. As it turns out, many of them would have to add a substantial amount of travel distance and travel time to their commutes (as much as fourteen miles and two hours in the most extreme cases), even if they used the “best” trip recommendation possible provided by OTP 1.5. This might be caused by waiting long times for transfers, spending time on walking from point to point, and/or boarding transit vehicles which take long and indirect routes towards the HQ.

To narrow down the pool of potential commuters, the issue of how a “Walk + Transit + Walk” trip can be deemed “competitive” with driving had to be addressed. One possible metric for “competitiveness” can be found in the Transit Capacity and Quality of Service Manual (TCQSM)’s Index of Transit-Auto Travel Time Ratio(s) (see Figure 39). This ratio index is used to evaluate the extent to which an alternative trip involving transit is tolerable or tedious from a passenger perspective. The higher the ratio, the less likely that a commuter will bother to switch to a transit-based trip. Based on this index, an initial limit of 2 was chosen as a cut-off point; a transit-based trip with an equal or lesser ratio value is assumed to still be tolerable. Although 2 might seem like a high number, this limit allows for the inclusion of cases where initial driving times are small e.g. 15 minutes for driving versus 30 minutes for a “Walk + Transit + Walk” trip, where the latter may still be doable in practice even if the ratio is high. In addition, for the TCQSM ratio calculations, the value of travel time for driving in traffic congestion was used to reflect the fact that commuters would be leaving for work during the morning peak.
With these conditions set, the pool of potential “Walk + Nearest Transit + Walk” commuters shrunk rather dramatically to a total of 81 persons (2.6% out of 3,136 employees). This new pool was used for further analysis in the following sections, rather than the earlier pool.

The home locations of the 81 employees are shown in Figure 40 below.
Figure 40: Employees Identified as Potential “Walk + Nearest Transit + Walk” Commuters

5.2.4.2 “Walk + Nearest Transit + Walk” Distance from Home Locations to the HQ

Figure 41 shows the distribution of the values for the additional travel distance that a “Walk + Nearest Transit + Walk” trip adds to an employee’s commute versus a driving trip, derived for...
each of the 81 persons in the new pool of potential commuters. Compared to the earlier pool, the range of travel distances added to commute trips is much smaller (with barely any miles added). Interestingly, there are some employees who would even have a few miles shaved off their trip.

![Figure 41: Additional Travel Distance for “Walk + Nearest Transit + Walk” Trips vs. Driving](image)

5.2.4.3 “Walk + Nearest Transit + Walk” Travel Time from Home Locations to the HQ

Figure 42 shows the distribution of values for the additional travel time that a “Walk + Nearest Transit + Walk” trip adds to an employee’s commute versus a driving trip in non-congested conditions. Meanwhile, Figure 43 shows the distribution of values for the additional travel time that a “Walk + Nearest Transit + Walk” trip adds to an employee’s commute versus a driving trip in congested conditions. As expected, taking a “Walk + Nearest Transit + Walk” trip adds on more time to a commute trip versus driving. However, if traffic congestion is present, the gap may be narrowed somewhat.
Figure 42: Additional Travel Time for “Walk + Nearest Transit + Walk” Trips vs. Driving in Uncongested Traffic

Figure 43: Additional Travel Time for “Walk + Nearest Transit + Walk” Trips vs. Driving in Traffic Congestion
Figure 44 shows the range of travel times for “Walk + Nearest Transit + Walk” trips versus driving in congested conditions. The median value for “Walk + Nearest Transit + Walk” trips is 36 minutes; the median value for driving in congested conditions is 21 minutes.

![Graph showing travel times for Walk + Nearest Transit + Walk vs. driving in traffic congestion.](image)

**Figure 44: Travel Time for “Walk + Nearest Transit + Walk” Trips vs. Driving in Traffic Congestion**

Figure 45 shows where potential “Walk + Nearest Transit + Walk” commuters live and is color-coded according to the amount of travel time that is added to their commute, if they take a “Walk + Nearest Transit + Walk” trip instead of driving in traffic congestion. The map shows that distance from home to HQ is not necessarily correlated with the amount of additional travel time spent on this mode choice. Rather, it may depend on the employee’s proximity to a transit stop and other factors affecting the speed of travel.
Figure 45: Map of Potential “Walk + Nearest Transit + Walk” Commuters According to Additional Travel Time for “Walk + Nearest Transit + Walk” Trips vs. Driving in Traffic Congestion
5.2.5 Drive + Express/Commuter Bus + Walk

5.2.5.1 Employees Identified as Potential “Drive + Express/Commuter Bus + Walk” Commuters

For an employee to even consider taking an express/commuter bus, a Park-and-Ride facility must be within their reach first and foremost. As detailed earlier, OTP 1.5’s isochrone function was used to draw a catchment area around individual Park-and-Ride facilities and identify employees within a 30-minute-drive (in free-flow conditions) of said facility. For each identified employee, the nearest two express/commuter Park-and-Ride facilities were located so as to obtain trip recommendations and travel time estimates from start to finish. Next, a single trip recommendation and affiliated Park-and-Ride facility for each employee was finalized based on which option had the shortest travel time.

In total, 2,564 out of 3,136 employees or 82% were initially identified as being able to access a “Drive + Express/Commuter Bus + Walk” option. Figure 46 below shows the approximate home locations of these employees.
That said, a sanity check performed on the trip data for this initial pool suggested that many of the 2,564 commuters would find this mode choice rather unworkable. As it turns out, many of
them would have to add an excessive amount of travel distance and travel time to their commutes (as much as forty miles and one and a half hours in the most extreme cases). This is most likely due to the catchment area for each Park-and-Ride facility being overly generous and also not being restricted by the directionality of travel. In other words, the catchment areas readily capture employees who would have to drive out of their way to reach a Park-and-Ride facility (even if this means driving in the opposite direction from the HQ / Downtown Atlanta).

To narrow down the pool of potential commuters, the TQCSM ratio index was used to evaluate the competitiveness of this mode choice relative to driving (in traffic congestion). With a ratio value of 2 as a cut-off point, this leaves a potential pool of 985 commuters (31.4% of 3,136 employees). This new pool was used for further analysis in the following sections, rather than the earlier pool. Figure 47 below shows the home locations of these employees. The new geographic distribution of the potential commuters in Figure 47 suggests that the more cumbersome trips have been successfully filtered out.
5.2.5.2 “Drive + Express/Commuter Bus + Walk” Distance from Home Locations to the HQ

Figure 48 shows the distribution of values for the additional travel distance that a “Drive + Express/Commuter Bus + Walk” trip adds to an employee’s commute versus a driving trip. While
the range here is much less than the range of distances for the initial pool prior to filtering via the TCQSM ratio index, there are evidently still commuters who would have to add many more miles to their commute. This suggests that some employees may still have to drive out of their way to a Park-and-Ride facility, if they use this mode choice.

Figure 48: Additional Travel Distance for “Drive + Express/Commuter Bus + Walk” Trips vs. Driving

5.2.5.3 “Drive + Express/Commuter Bus + Walk” Travel Time from Home Locations to the HQ

Figure 49 shows the distribution of values for the additional travel time that a “Drive + Express/Commuter Bus + Walk” trip adds to an employee’s commute versus a driving trip in non-congested conditions. Figure 50 shows the distribution of values for the additional travel time that a “Drive + Express/Commuter Bus + Walk” trip adds to an employee’s commute versus a driving trip in congested conditions.
Figure 49: Additional Travel Time for “Drive + Express/Commuter Bus + Walk” Trips vs. Driving in Uncongested Traffic

Figure 50: Additional Travel Time for “Drive + Express/Commuter Bus + Walk” Trips vs. Driving in Traffic Congestion
The range of values for both Figure 49 and Figure 50 suggest that for some commuters, switching to “Drive + Express/Commuter Bus + Walk” trips will add a lot of time to their commutes, though traffic congestion may dampen these effects. A key reason for this is the time spent on particular legs of the trip, as follows:

- **Express/commuter bus trip legs**: Even the shortest express/commuter bus ride to Downtown Atlanta consumes 35 minutes (starting at Town Center Park-and-Ride), while the longest rides consume 104 minutes (starting at Floyd and Snellville Park-and-Ride facilities) inclusive of waiting time. This means that even if the first mile and last mile legs (“Drive to the Park-and-Ride” and “Walk to the HQ”) are excluded or made faster somehow, there is still a fixed (and even lengthy) amount of time that a commuter has to spend on the express/commuter bus leg alone;

- **Walk trip legs**: Many express/commuter buses stop at the Civic Center MARTA station or in Downtown Atlanta; these locations are the stops closest to the HQ. The walk from these locations to the HQ generally takes about 19 minutes or more according to Google Maps. (At present, the HQ Shuttle Bus helps to shorten the journey from 19 minutes to about 7 minutes on average; however, since the interval between buses is around 15 minutes, a worker who just missed the last HQ Shuttle Bus would find their total waiting and travel time via the next HQ Shuttle Bus to be about the same as walking to the HQ);

- **Transfer and wait times**: Some commuters would have to transfer to a second bus or rail line to get to the HQ, which adds about 20 minutes of time spent on waiting. This affects commuters who use CobbLinc express/commuter buses (which stop at the H.E.
Holmes MARTA station), Xpress buses leaving from McDonough Park-and-Ride, and MARTA buses leaving from Mansell and Windward Park-and-Ride.

Interestingly, there are also a number of employees for whom travel times would actually be reduced as opposed to driving in traffic congestion.

Figure 51 below shows the range of travel times for “Drive + Express/Commuter Bus + Walk” versus driving in congested conditions. Generally, the median value for “Drive + Express/Commuter Bus + Walk” trips is 77 minutes while the median value for driving in congested conditions is 51 minutes.

![Figure 51: Travel Time for “Drive + Express/Commuter Bus + Walk” Trips vs. Driving in Traffic Congestion](image)

Figure 51 shows the home locations of potential “Drive + Express/Commuter Bus + Walk” commuters, color-coded according to the amount of travel time added to one’s commute for a “Drive + Express/Commuter Bus + Walk” trip versus driving in congested conditions. Per the map
in Figure 52, the distance from the home to the HQ is not necessarily correlated with the amount of additional travel time spent on this mode choice. Rather, it may depend on the employee’s proximity to a Park-and-Ride facility and other factors affecting the speed of travel. There are even employees who would see a reduction in travel time, if they use this mode choice instead of driving in traffic congestion.
Figure 52: Map of Potential “Drive + Express/Commuter Bus + Walk” Commuters According to Additional Travel Time for “Drive + Express/Commuter Bus + Walk” Trips vs. Driving in Traffic Congestion
5.2.6 Drive + MARTA Rail + Walk

5.2.6.1 Employees Identified as Potential “Drive + MARTA Rail + Walk” Commuters

Similar to the “Drive + Express/Commuter Bus + Walk” mode choice, the answer to whether this mode choice is possible for employees depends on whether a MARTA rail station is within reach in the first place. As detailed earlier, Google Places API was used to identify the two nearest MARTA rail stations for each employee. Trip recommendations and travel time estimates from start to finish were obtained for each option, and a final trip recommendation based on shortest travel time was determined for each employee. In total, 1,177 out of 3,136 employees or 38% were initially identified as possible candidates for a “Drive + MARTA Rail + Walk” trip. Figure 53 below shows where these employees live.
A sanity check was performed on the trip data for this initial pool of 1,177 employees. Its findings suggested that the criteria for identifying potential commuters could be tightened up.
further, as some commuters were shown to experience a sizeable increase in travel distances and travel times with this option. One reason may be that some employees would have to drive out of their way to reach a MARTA rail station as opposed to driving directly to the HQ.

For further filtering, the TCQSM ratio index was used again as a metric of competitiveness and a convenient way to filter out longer trips. With a ratio of 2 as the cut-off point, this results in a potential pool of 788 commuters (25% of 3,136 employees). This new pool was used for further analysis in the following sections, rather than the earlier pool. Figure 54 below shows the home locations of these employees.
5.2.6.1 “Drive + MARTA Rail + Walk” Distance from Home Locations to the HQ

Figure 55 shows the distribution of values for the additional travel distance that a “Drive + MARTA Rail + Walk” trip adds to an employee’s commute versus a driving trip. Interestingly,
the distribution is relatively normal-shaped, with a large number of employees not seeing much of a difference in their commute distance.

![Figure 55: Additional Travel Distance for “Drive + MARTA Rail + Walk” Trips vs. Driving](image)

5.2.6.2 “Drive + MARTA Rail + Walk” Travel Time from Home Locations to the HQ

Figure 56 shows the distribution of values for the additional travel time that a “Drive + MARTA Rail + Walk” trip adds to an employee’s commute versus a driving trip in non-congested conditions. Figure 57 shows the distribution of values for the additional travel time that a “Drive + MARTA Rail + Walk” trip adds to an employee’s commute versus a driving trip in congested conditions. As expected, many employees experience an increase in travel times when using this mode choice versus driving in traffic congestion.
Figure 56: Additional Travel Time for “Drive + MARTA Rail + Walk” Trips vs. Driving in Uncongested Traffic

Figure 57: Additional Travel Time for “Drive + MARTA Rail + Walk” Trips vs. Driving in Traffic Congestion
Figure 58 below shows the range of travel times for “Drive + MARTA Rail + Walk” trips versus driving in congested conditions. The median value for “Drive + MARTA Rail + Walk” trips is 41 minutes while the median value for driving in congested conditions is 25 minutes.

Figure 58: Travel Time for “Drive + MARTA Rail + Walk” Trips vs. Driving in Traffic Congestion

Figure 59 shows the home locations of potential “Drive + MARTA Rail + Walk” commuters, color-coded according to the amount of travel time added to one’s commute for a “Drive + MARTA Rail + Walk” trip versus driving in congested conditions. Per the map, the distance from home to HQ is not necessarily correlated with the amount of additional travel time spent on this mode choice. Rather, it may depend on the employee’s proximity to a MARTA rail station and other factors affecting the speed of travel.
Figure 59: Map of Potential for “Drive + MARTA Rail + Walk” Commuters According to Additional Travel Time for “Drive + MARTA Rail + Walk” Trips vs. Driving in Traffic Congestion
5.2.7 Bike + MARTA Rail + Bike

5.2.7.1 Employees Identified as Potential “Bike + MARTA Rail + Bike” Commuters

This mode choice options relies on MARTA rail and is therefore near-identical to the “Drive + MARTA Rail + Walk” mode choice option, although it assumes that the employee in question uses a bicycle to get to and from the MARTA rail station. However, it is likely that not everyone will want to cycle the same distance that they would have to drive to a MARTA rail station. Because of this, a 5-mile limit for cycling distance from an employee’s home to the nearest MARTA rail station is imposed as a cut-off point. Based on the TCQSM ratio index, a ratio of 2 is also imposed as another cut-off point. This results in a total of 532 persons who meet both these criteria (or 17% of all employees). This also comprises 45% of the original total of 1,177 employees previously identified as potential “Drive + MARTA Rail + Walk” commuters. Figure 60 below shows the home locations of these employees.
Figure 60: Employees Identified as Potential “Bike + MARTA Rail + Bike” Commuters

5.2.7.2 “Bike + MARTA Rail + Bike” Distance from Home Location to HQ

Figure 61 shows the distribution of values for the additional travel distance that a “Bike + MARTA Rail + Bike” trip adds to an employee’s commute versus a driving trip. Interestingly, the
distribution is relatively normal-shaped, with many employees not seeing much of a difference in their commute distance.

![Histogram showing additional travel distance for "Bike + MARTA Rail + Bike" trips vs. driving.](image)

**Figure 61: Additional Travel Distance for “Bike + MARTA Rail + Bike” Trips vs. Driving**

5.2.7.3 “Bike + MARTA Rail + Bike” Travel Time from Home Location to HQ

Figure 62 shows the distribution of values for the additional travel time that a “Bike + MARTA Rail + Bike” trip adds to an employee’s commute versus a driving trip in non-congested conditions. Figure 63 shows the distribution of values for the additional travel time that a “Bike + MARTA Rail + Bike” trip adds to an employee’s commute versus a driving trip in congested conditions. As expected, many employees experience an increase in travel times when using this mode choice versus driving in traffic congestion. The amount of time added in some cases is rather sizable, which is understandable since biking to a MARTA rail station would usually take more time than driving there.
Figure 62: Additional Travel Time for “Bike + MARTA Rail + Bike” Trips vs. Driving in Uncongested Traffic

Figure 63: Additional Travel Time for “Bike + MARTA Rail + Bike” Trips vs. Driving in Traffic Congestion
Figure 64 below shows the range of travel times for “Bike + MARTA Rail + Bike” trips versus driving in congested conditions. The median value for “Bike + MARTA Rail + Bike” trips is 40 minutes; the median value for driving in congested conditions is 24 minutes.

![Figure 64: Travel Time for “Bike + MARTA Rail + Bike” Trips vs. Driving in Traffic Congestion](image)

Figure 65 shows the home locations of potential “Bike + MARTA Rail + Bike” commuters, color-coded according to the amount of travel time added to one’s commute for a “Bike + MARTA Rail + Bike” trip versus driving in congested conditions. Per the map, the distance from home to HQ is not necessarily correlated with the amount of additional travel time spent on this mode choice. Rather, it may depend on the employee’s proximity to a MARTA rail station and other factors affecting the speed of travel.
Figure 65: Map of Potential “Bike + MARTA Rail + Bike” Commuters According to Additional Travel Time for “Bike + MARTA Rail + Bike” Trips vs. Driving in Traffic Congestion
5.2.8 Walk + MARTA Rail + Walk

5.2.8.1 Employees Identified as Potential “Walk + MARTA Rail + Walk” Commuters

This mode choice options relies on MARTA rail and is thus near-identical to the “Drive + MARTA Rail + Walk” mode choice option, though it assumes that the employee in question would walk to get to and from the MARTA rail station instead of drive. However, not everyone would want to walk the same distance that they would have to drive to a MARTA rail station. Because of this, a limit of $1 \frac{1}{2}$ miles in walking distance to the MARTA station is imposed, based on the research literature that commuters may walk longer distances to take rail rather than bus services (U.S. Department of Transportation 2013). The cutoff limit of $1 \frac{1}{2}$ miles differentiates this “Walk + MARTA Rail + Walk” mode choice from the earlier “Walk + Nearest Transit + Walk” mode choice, where the latter’s cutoff limit is $\frac{3}{4}$ in walking distance and may involve bus trips, rail trips, and/or a combination of bus and rail trips.

In addition, based on the TCQSM ratio index, a ratio of 2 is imposed as another cut-off point. This results in a total of 46 persons meeting this criteria (or 1.5% of all employees), which also comprises 4% out of the 1,177 employees identified as potential “Drive + MARTA Rail + Walk” commuters in the previous sections. Figure 66 below shows the home locations of these employees.
Figure 66: Employees Identified as Potential “Walk + MARTA Rail + Walk” Commuters

5.2.8.2 “Walk + MARTA Rail + Walk” Distance from Home Locations to the HQ

Figure 67 shows the distribution of values for the additional travel distance that a “Walk + MARTA Rail + Walk” trip adds on to an employee’s commute versus a driving trip. Interestingly,
the distribution is relatively normal-shaped, with a large number of employees not seeing much of a difference in their commute distance.

![Figure 67: Additional Travel Distance for “Walk + MARTA Rail + Walk” Trips vs. Driving](image)

5.2.8.3 “Walk + MARTA Rail + Walk” Travel Time from Home Locations to the HQ

Figure 68 shows the distribution of values for the additional travel time that a “Walk + MARTA Rail + Walk” trip adds to an employee’s commute versus a driving trip in non-congested conditions. Figure 69 shows the distribution of values for the additional travel time that a “Walk + MARTA Rail + Walk” trip adds to an employee’s commute versus a driving trip in congested conditions. As expected, many employees experience a substantial increase in travel times when using this mode choice versus only driving.
Figure 68: Additional Travel Time for “Walk + MARTA Rail + Walk” Trips vs. Driving in Uncongested Traffic

Figure 69: Additional Travel Time for “Walk + MARTA Rail + Walk” Trips vs. Driving in Traffic Congestion
Figure 70 below shows the range of travel times for “Walk + MARTA Rail + Walk” versus driving in congested conditions. The median value for “Walk + MARTA Rail + Walk” trips is 42 minutes while the median value for driving in congested conditions is 23 minutes.

Figure 70: Travel Time for “Walk + MARTA Rail + Walk” Trips vs. Driving in Traffic Congestion

Figure 71 shows the home locations of potential “Walk + MARTA Rail + Walk” commuters, color-coded according to the amount of travel time added to one’s commute for a “Walk + MARTA Rail + Walk” trip versus driving in congested conditions. Per the map, the distance from home to HQ is not necessarily correlated with the amount of additional travel time spent on this mode choice. Rather, it may depend on the employee’s proximity to a MARTA rail station and other factors affecting the speed of travel.
Figure 71: Map of Potential “Walk + MARTA Rail + Walk” Commuters According to Additional Travel Time for “Walk + MARTA Rail + Walk” Trips vs. Driving in Traffic Congestion
5.3 Comparison of All Alternative Mode Choices versus Driving

Thus far, the breakdown of different mode choices and the pool of potential commuters for each is shown in Table 15:

<table>
<thead>
<tr>
<th>No.</th>
<th>Mode Choice</th>
<th>Criteria</th>
<th>Employees</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Total</td>
</tr>
<tr>
<td>1</td>
<td>Drive</td>
<td>• N/A</td>
<td>3,136</td>
</tr>
<tr>
<td>2</td>
<td>Bike</td>
<td>• &lt;= 5 miles biking distance between home and HQ</td>
<td>408</td>
</tr>
<tr>
<td>3</td>
<td>Walk</td>
<td>• &lt;= 1.5 miles walking distance between home and HQ</td>
<td>41</td>
</tr>
<tr>
<td>4</td>
<td>Walk + Nearest Transit + Walk</td>
<td>• Trip recommendation from OTP 1.5 • &lt;= 2 ratio value per TCQSM index</td>
<td>81</td>
</tr>
<tr>
<td>5</td>
<td>Drive + Express / Commuter Bus + Walk</td>
<td>• Nearest Park-and-Ride facility identified • Trip recommendation from OTP 1.5 • &lt;= 2 ratio value per TCQSM index</td>
<td>985</td>
</tr>
<tr>
<td>6</td>
<td>Drive + MARTA Rail + Walk</td>
<td>• Nearest MARTA rail station identified • &lt;= 2 ratio value per TCQSM index</td>
<td>788</td>
</tr>
<tr>
<td>7</td>
<td>Bike + MARTA Rail + Bike</td>
<td>• Nearest MARTA rail station identified • &lt;= 5 miles walking distance between home and MARTA rail station • &lt;= 2 ratio value per TCQSM index</td>
<td>532</td>
</tr>
<tr>
<td>8</td>
<td>Walk + MARTA Rail + Walk</td>
<td>• Nearest MARTA rail station identified • &lt;= 1.5 miles walking distance between home and MARTA rail station • &lt;= 2 ratio value per TCQSM index</td>
<td>46</td>
</tr>
</tbody>
</table>

From Table 15, some mode choices appear to have more reach in terms of potential numbers of users. This is especially true for mode choices involving driving, as this allows a wider net to be cast geographically. That said, for employees with multiple mode choices available, there
may be a particular mode that suits them best depending on where they live. The next section thus aims to identify the “best” alternative mode for each employee.

5.4 “Best” Alternative Mode for Each Employee

For each employee in the dataset, all finalized alternative commute mode choices available were compared and the “best” alternative was selected in this manner:

(i) Select the commute mode with the lowest ratio value (under 2);
(ii) If there are no commute modes with a ratio value of under 2, check if the employee is able to use a Bike or Walk single-mode option, and select either Bike or Walk depending on which has the lowest ratio value out of both.

In general, Bike or Walk ratio values may be higher than 2 since their travel speeds are much slower compared to driving. However, since the travel distances for Bike and Walk have already been capped at 5 miles and 1.5 miles respectively (i.e. for employees living close to the HQ), these options are still presumed to be doable for employees who have been identified.

Per Table 16, the “best options” for each employee were grouped according to various TCQSM ratio thresholds. The higher the TCQSM ratio threshold, the larger the number of employees with an identified alternative commute mode. Of course, a higher ratio means that the alternative commute mode takes a longer travel time and may be less attractive when attempted in reality.
Table 16: Best Alternative Commute Modes for Employees According to TCQSM Ratio

<table>
<thead>
<tr>
<th>No.</th>
<th>Alternative Name</th>
<th>Ratio of &lt;= 1 or Bike/Walk</th>
<th>Ratio of &lt;= 1.5 or Bike/Walk</th>
<th>Ratio of &lt;= 1.75 or Bike/Walk</th>
<th>Ratio of &lt;= 2 or Bike/Walk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Total (%)</td>
<td>Total (%)</td>
<td>Total (%)</td>
<td>Total (%)</td>
</tr>
<tr>
<td>1</td>
<td>No Alternative Commute Mode</td>
<td>2,665 85%</td>
<td>2,052 65%</td>
<td>1,513 48%</td>
<td>1,089 35%</td>
</tr>
<tr>
<td>2</td>
<td>An Alternative Commute Mode</td>
<td>471 15%</td>
<td>1,084 35%</td>
<td>1,623 52%</td>
<td>2,047 65%</td>
</tr>
<tr>
<td></td>
<td>Bike</td>
<td>408 13%</td>
<td>398 13%</td>
<td>389 12%</td>
<td>384 12%</td>
</tr>
<tr>
<td></td>
<td>Walk</td>
<td>0 0%</td>
<td>0 0%</td>
<td>0 0%</td>
<td>0 0%</td>
</tr>
<tr>
<td></td>
<td>Walk + Nearest Transit + Walk</td>
<td>0 0%</td>
<td>1 0%</td>
<td>3 0%</td>
<td>3 0%</td>
</tr>
<tr>
<td></td>
<td>Drive + Express/Commuter Bus + Walk</td>
<td>63 2%</td>
<td>381 12%</td>
<td>695 22%</td>
<td>977 31%</td>
</tr>
<tr>
<td></td>
<td>Drive + MARTA Rail + Walk</td>
<td>0 0%</td>
<td>244 8%</td>
<td>432 14%</td>
<td>548 17%</td>
</tr>
<tr>
<td></td>
<td>Bike + MARTA Rail + Bike</td>
<td>0 0%</td>
<td>60 2%</td>
<td>104 3%</td>
<td>135 4%</td>
</tr>
<tr>
<td></td>
<td>Walk + MARTA Rail + Walk</td>
<td>0 0%</td>
<td>0 0%</td>
<td>0 0%</td>
<td>0 0%</td>
</tr>
</tbody>
</table>

As noted earlier, a Bike or Walk commute mode is considered to be the “best option” if it is the only one available after other options have been screened out; however, Walk trips are always beaten by Bike trips in terms of travel time and thus have 0 recommendations across all ratio categories in Table 16. When going from a ratio of <=1 to a ratio of <=1.5 in Table 16, the number of Bike trips declines slightly as other alternatives involving MARTA rail are opened up to commuters.

As for the “Walk + Nearest Transit + Walk” mode choice, it becomes the best alternative for exactly 1 person when a ratio of <= 1.5 is used. A deeper dive into this particular trip...
recommendation reveals that the person in question ("Employee A") lives right next to a MARTA bus stop (taking less than a minute to walk to it), and that the MARTA bus route in question travels on a major arterial road in an near-straight line with practically no detours, heading directly to the MARTA rail station nearest to the HQ. When a ratio of \( \leq 1.75 \) is used, the "Walk + Nearest Transit + Walk" mode choice becomes the best alternative for 2 more employees ("Employee B" and "Employee C"); for both these employees, OTP actually recommends taking the exact same bus route as Employee A. This situation suggests that this particular bus route works well for employees who can access it, since it offers an almost door-to-door connection to the HQ.

Otherwise, from the results of Table 16, it appears that employees interested in transit-based options are better served by express/commuter buses and connections to MARTA rail as opposed to local buses. There are a number of ways to get to MARTA rail stations, but driving or biking there certainly is faster and covers longer distances versus walking, which results in 0 recommendations for the "Walk + MARTA Rail + Walk" option across all ratio categories.

Figure 72, Figure 73, Figure 74, and Figure 75 show the home locations of employees and their "best options" for alternative commute modes, according to their respective TCQSM ratio groups as per Table 16.
Per Figure 72, the only alternative commute mode that may actually be faster than driving in traffic congestion for some employees is the “Drive + Express/Commuter Bus + Walk” mode choice. There are five Park-and-Ride facilities for which this situation applies: Dacula, Hamilton, Mall of Georgia, Town Center and Woodstock Park-and-Ride(s).
Figure 73: Best Alternative Commute Modes, Ratio of <= 1.5 or Bike/Walk

Per Figure 73, as the TCQSM ratio threshold is increased to 1.5, this opens up options for other employees, namely those involving MARTA rail services. As noted earlier, the “Walk + Nearest Transit + Walk” option becomes a “best alternative” to exactly one person (though it does not appear to be present on the map at this scale).
Figure 74: Best Alternative Commute Modes, Ratio of $\leq 1.75$ or Bike/Walk

Per Figure 74, with a TCQSM ratio threshold of 1.75, more commuters are deemed to have a “best” alternative commute option available. Again, the caveat is that this likely means a higher travel time for these persons.
Figure 75: Best Alternative Commute Modes, Ratio of $\leq 2$ or Bike/Walk

Figure 75 shows the map of employee home locations if a TCQSM ratio threshold of 2 is applied. A cluster of employees in southwest Metro Atlanta is shown to have “Drive + Express/Commuter Bus + Walk” as their best option, but this would mean travel times of nearly twice as much as driving in traffic congestion, so this should be taken with a grain of salt.
5.5 Employer HQ’s Mode Share versus Potential Alternative Commuting Market

One of the major dilemmas for the HQ Commutes Team is how best to determine the current mode share at the HQ, in order to set a benchmark for improvement. Previous mode share estimates have suggested that as many as 90% of the HQ’s worker population drives alone to work, although the origin and context behind these estimates is unknown (Greenwald 2019, 67). Generally, this task is complicated by the lack of technological systems set up for this purpose, variability in the HQ’s worker population over time, and data quality issues.

As part of the feasibility analysis, an attempt was made to estimate mode share using badge-in data, which is the only type of data that tracks personnel movements at the HQ. Namely, the company’s badge data system records when and where people use their badges to access doors and entrances / exits at worksites. The main purpose of this data system is to maintain workplace safety and security, by making sure that only people with company-issued badges are able to access the HQ, or that certain areas are kept off-limits depending on the person’s access clearance level. Information recorded by the system includes the date and time of access, the name and details of the access point, the person’s name and department, and sometimes their badge status (i.e. whether they are an employee, contingent worker, or special affiliate) if this information is available. The system does not record how the person arrived there (i.e. the mode of travel that they used to reach that access point), since it has no way of knowing this. However, for the purpose of making an educated guess about a person’s commuting behavior, some reasonable assumptions can be made. If the badge system records a parking gate as a person’s first badge-in location of the day, it can be assumed that they arrived via a personal vehicle; and correspondingly, if a person’s first badge-in location is anywhere else (e.g. a street-facing main entrance), it can be assumed that they did not arrive in a personal vehicle on that day.
For further analysis, badge-in data records for the first two weeks in March 2020, excluding weekends, were examined. These two weeks were selected for analysis as later workweeks were disrupted by the COVID-19 pandemic, during which the HQ shut down and the majority of HQ-assigned workers were allowed to work from home temporarily.

Based on the two weeks of data, the following patterns were discovered:

(i) During a 24-hour time period of a typical workday, most people’s first badge-in activities occurred between 6am and 10am. The time range which usually saw the most activity was 7:30am through 9:00am; in other words, most HQ-assigned persons arrived at the HQ during this time period;

(ii) For mornings (i.e. 6am through 10am), the estimated percentage of people who arrived by non-driving means (i.e. their first badge-in access point of the day was not at a parking gate) was consistently around 13%. This occurred even when the total number of people present on-site fluctuated between days.

The full breakdown of the 2 weeks of badge-in activity at the HQ is shown in Table 17. The badge-in levels for Tuesday, 10 March 2020 were unusually low as that day was used as a “special closure” day to test out work-from-home arrangements. Badge-in data outside the 6am through 10am range was ignored for the purpose of the analysis. This decision to exclude the badge-in data outside the 6am through 10am range was due to two reasons, i.e. (i) there is a chance that the people whose first badge-ins of the day were during 12am and 6am may actually be night-shift workers who had arrived the night before, and/or (ii) the people whose first badge-ins of the day were after 10am might be using alternative work hour arrangements, working remotely or part-time, or even stopping by at the HQ briefly for meetings and events.
One caveat about Table 17 is that the data source does not always contain complete information on people’s records, i.e. their assigned office location and/or their badge status as an employee, contingent worker or special affiliate. Some of this is due to system issues or lack of records in the company’s HR data systems. Because of this, the numbers in Table 17 likely include workers from other office locations who may be stopping by the HQ for whatever reason. However, it is still important to count them as part of the HQ mode share since they would be using HQ commuting facilities, e.g. parking spaces. In addition, it is not clear how many HQ-assigned persons were absent on certain days due to teleworking arrangements versus other reasons such as being away on vacation/sick leave, working at other offices/company locations, traveling for work, working in a role that did not require daily presence at the HQ, and so on.

**Table 17: Estimated Mode Share for Morning Hours (6AM-10AM), First Two Weeks of March 2020, Based on Data for First Badge-In Access Points of the Day**

<table>
<thead>
<tr>
<th>Category</th>
<th>Monday, 2 March</th>
<th>Tuesday, 3 March</th>
<th>Wednesday, 4 March</th>
<th>Thursday, 5 March</th>
<th>Friday, 6 March</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Badge-Ins</strong></td>
<td>Total</td>
<td>%</td>
<td>Total</td>
<td>%</td>
<td>Total</td>
</tr>
<tr>
<td>All (24 Hours)</td>
<td>3,834</td>
<td>100</td>
<td>4,002</td>
<td>100</td>
<td>3,886</td>
</tr>
<tr>
<td>Morning (6-10AM)</td>
<td>3,022</td>
<td>79</td>
<td>3,174</td>
<td>79</td>
<td>3,063</td>
</tr>
<tr>
<td>Morning Peak (7:30-9AM)</td>
<td>1,999</td>
<td>52</td>
<td>1,971</td>
<td>49</td>
<td>1,956</td>
</tr>
<tr>
<td><strong>Morning (6-10AM)</strong></td>
<td>Total</td>
<td>%</td>
<td>Total</td>
<td>%</td>
<td>Total</td>
</tr>
<tr>
<td>Driving Commuters</td>
<td>2,639</td>
<td>87</td>
<td>2,785</td>
<td>87</td>
<td>2,653</td>
</tr>
<tr>
<td>Non-Driving Commuters</td>
<td>383</td>
<td>13</td>
<td>389</td>
<td>13</td>
<td>410</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>3,022</td>
<td>100</td>
<td>3,174</td>
<td>100</td>
<td>3,063</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Category</th>
<th>Monday, 9 March</th>
<th>Tuesday, 10 March</th>
<th>Wednesday, 11 March</th>
<th>Thursday, 12 March</th>
<th>Friday, 13 March</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Badge-Ins</strong></td>
<td>Total</td>
<td>%</td>
<td>Total</td>
<td>%</td>
<td>Total</td>
</tr>
<tr>
<td>All (24 Hours)</td>
<td>3,856</td>
<td>100</td>
<td>345</td>
<td>100</td>
<td>3,880</td>
</tr>
<tr>
<td>Morning (6-10AM)</td>
<td>2,954</td>
<td>77</td>
<td>120</td>
<td>35</td>
<td>3,054</td>
</tr>
<tr>
<td>Morning Peak (7:30-9AM)</td>
<td>1,825</td>
<td>47</td>
<td>47</td>
<td>14</td>
<td>1,853</td>
</tr>
<tr>
<td><strong>Morning (6-10AM)</strong></td>
<td>Total</td>
<td>%</td>
<td>Total</td>
<td>%</td>
<td>Total</td>
</tr>
<tr>
<td>Driving Commuters</td>
<td>2,633</td>
<td>87</td>
<td>119</td>
<td>87</td>
<td>2,683</td>
</tr>
<tr>
<td>Non-Driving Commuters</td>
<td>321</td>
<td>13</td>
<td>1</td>
<td>13</td>
<td>371</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>2,954</td>
<td>100</td>
<td>120</td>
<td>100</td>
<td>3,054</td>
</tr>
</tbody>
</table>
5.6 Caveats of the Feasibility Analysis

Some caveats and limitations of the feasibility analysis performed thus far include:

(i) The feasibility analysis does not include contingent workers or special affiliates. The final dataset analyzed for mode choice comparisons consisted of 3,136 persons (using the HQ-assigned employee roster for March 2021). However, for that same month, the number of total HQ assignees was 5,569 persons, meaning that another 2,433 persons (44% of total assignees) of whom the majority are likely contingent workers, were not accounted for due to lack of data. While this issue is unfortunate, it could not be avoided. Importantly, there is potential for bias introduced into the analysis;

(ii) Potential for carpooling/rideshare is not considered. Greenwald (2019) in fact had performed an analysis on potential carpooling/rideshare prospects among HQ-based employees, hence it was felt that further analysis might be redundant. In addition, there are other factors that influence carpooling propensity, such as compatibility of work schedules and users’ comfort with sharing vehicle space with others who are from different households. With the COVID-19 pandemic disrupting commute routines and also leaving people with a general aversion to sharing space out of health concerns, it is difficult to say off the bat how many HQ-assigned workers would be comfortable carpooling and with whom. Further research on this issue is needed down the line;

(iii) Travel time and traffic congestion estimates for driving may have been affected by COVID-19. Per sources such as TomTom’s Traffic Index for Metro Atlanta, congestion levels were still shown to be less than pre-pandemic levels as of April
Since Google Distance Matrix API only takes into account the most recent weeks of traffic, there is a chance that the “pessimistic” traffic model parameter may still be underestimating the amount of time spent in traffic and therefore overestimating the speed of driving as a travel mode;

(iv) **Transit schedules (via GTFS) are in flux and may be updated over time.** Transit schedules and services may be upscaled or downsized depending on levels of user demand and agencies’ priorities, especially if finances are an issue due to the COVID-19 pandemic. This may affect the services available to commuters in the Metro Atlanta region in future;

(v) **Personnel changes such as workers leaving jobs, changing addresses, moving away, etc are almost certain to happen.** As such, this feasibility analysis should be considered a snapshot in time rather than a rigid prescription for the future;

(vi) **Not every worker has the latitude, interest or knowledge on how to switch from driving to an alternative commute mode.** Some people may respond more to persuasive arguments about reducing the detrimental impacts of car commuting on society, while some may be more swayed by an offer of a financial incentive. Others may be interested but find themselves unable to switch due to personal reasons, e.g. health issues, time-sensitive schedules, and/or prior commitments such as needing to send children to school or using cars for non-work errands. That said, this feasibility analysis focuses on travel times and distances as key points of consideration since many would-be alternative commuters in Metro Atlanta see these as key barriers (Georgia Commute Options 2020).
The ‘state of the commute’ in the near and distant future is uncertain, thanks to the COVID-19 pandemic. From mid-March 2020 onwards, the HQ was closed down to lessen the risk of disease spread among workers, and the majority of workers were allowed to work from home. This change led to a sharp drop in the number of workers who came to the HQ, which fell to a few hundred rather than a few thousand persons daily. It remains to be seen if the work-from-home arrangement will be retained by the major employer in later months or years, and how this would affect commuting patterns and commute modes in the future.

5.7 Recommendations for the Major Employer

If the most conservative scenario of the feasibility analysis is considered (i.e. a TCQSM ratio of 1 or less), the projected alternative commute mode share for employees is around 15% (as per Table 17 earlier). If the TCQSM ratio threshold is increased from 1 all the way to 2, the projected alternative commute mode share increases from anywhere between 35% to 65%. That said, the caveats noted in the section above suggest that these projections should be taken with a grain of salt. In addition, the estimated non-driving mode share of around 13% (as of March 2020) shows that some workers already use some forms of alternative commuting prior to the COVID-19 pandemic, though the precise breakdown according to mode is unknown. However, that number was relatively small, which suggests that more work is needed on the alternative commuting front.

Actions that the HQ Commutes Team may wish to consider include the following:

(i) Prioritizing the promotion of certain modes over others – such as biking and express/commuter bus routes – which, at the time that the feasibility analysis was conducted, appear to have the most promise in terms of sheer numbers of potential
commuters. Such efforts can be conducted via tailored outreach efforts such as surveys, pilot programs, and incentives targeting potential commuters;

(ii) For the “Bike” mode choice option, advocating and looking into improving biking infrastructure around the HQ and within the 5-mile biking distance range (HQ representatives may wish to work with the City of Atlanta for this purpose). More people may be attracted to biking if they feel that it is a safe activity, and biking infrastructure such as protected bike lanes may help with this;

(iii) For the “Walk + Nearest Transit + Walk” mode choice option, advocating for improvements to service quality and infrastructure (which are the jurisdiction of the transit providers as well as local and regional governments). At present, there is a lack of bus priority lanes in Metro Atlanta, meaning that local buses are likely to get bogged down by traffic congestion alongside private vehicles and that reliability and timeliness becomes an issue. Improvements on this front may help to improve bus travel times and make local buses a more attractive option;

(iv) For the “Drive + Express/Commuter Bus + Walk” mode choice option, ensuring that the connection between the HQ and the Civic Center MARTA station (or wherever express/commuter buses stop to let off HQ-bound commuters) is as speedy as seamless as possible. This is important because express/commuter buses seem to be a viable option for many potential commuters, but the last leg of the trip involves a walk of about 19 minutes or more to the HQ which may be a turn-off for commuters. As of March 2020, the HQ Shuttle Bus helped ferry commuters between the Civic Center MARTA Station and the HQ. However, further improvements could be made to the HQ Shuttle Bus such as advocating for bus
priority lanes (so that the HQ Shuttle Bus does not get bogged down in traffic), adjusting the timing of the HQ Shuttle Bus so that it arrives in time to pick up express/commuter bus users upon their arrival as opposed to making users wait, and so on. This issue may warrant further research and study;

(v) Advocating for work-from-home arrangements as an alternative commute mode, as opposed to requiring the worker to make a trip to the HQ at all. Teleworking can help to dramatically reduce pressure on parking facilities, as seen through the typical HQ on-site population numbers on Fridays before COVID-19, and also during the HQ shutdown induced by COVID-19 itself. That said, there is a possibility that workers who telework on certain days may still choose to drive to work on other days;

(vi) Conducting research and outreach to discern the exact barriers which workers face and/or the incentives that might get them to switch modes, especially for workers for whom certain alternative modes have been identified;

(vii) Improving data collection and data tracking systems, especially in terms of gauging the commute mode that a worker uses to arrive to the HQ. This includes installing and using vehicle counters, parking occupancy counters, and perhaps even badge-in or login systems that specifically record the commute mode that the worker in question used for that day. These tracking systems can in tandem with incentive-based systems, for example to award points or cash rewards for using an alternative mode versus imposing a penalty for driving. Seattle Children’s Hospital, which is a well-known success case in the employer TDM community, uses such a system
to effectively administer daily incentives tied to a person’s mode choice for the day (King County 2017); and

(viii) Redoing this feasibility analysis in future when conditions are ‘back to normal’; this may be whenever the COVID-19 pandemic has subsided, traffic levels and transit schedules in Metro Atlanta have stabilized, and/or the HQ reopens on a more permanent basis. If and when employees begin to commute to work again on a more regular basis, the HQ Commutes Team may have a better idea of commute patterns and mode share, and the process outlined in this feasibility analysis may be used again to determine the viability of commute options programs and which mode choices would net the best returns.
CHAPTER 6: CONCLUSION

Employee-based commute options programs have emerged as a way for employers to encourage their workers to use alternative commute modes rather than driving to work. There are many reasons for doing so, rooted in a history of public and private sector efforts to combat the detrimental effects of car commuting on larger society, road congestion, public health and the environment. At the employer level, the employer may also take up commute options programs as a way to lessen demand on parking spaces and infrastructure costs, among other reasons. That said, the effectiveness of commute options programs differs from place to place; key intervening factors include the availability of cheap parking, and also the availability and accessibility of alternative commute modes in the region and within the workers’ reach.

This analysis, through mapping out the home locations of employees at a major Metro Atlanta employer and obtaining alternative commute trip recommendations as well as travel time and distance details for each, evaluated the feasibility of various modes that were available. The evaluation found that the options available are very much dependent on where employees live. In addition, it is not enough to just have alternative commute mode options available, but their competitiveness and appeal relative to driving alone must also be considered before they can be touted as realistic prospects for commuters.

Ironically, in the case of Metro Atlanta – which is infamous for sprawl and traffic congestion and its residents’ overwhelming tendency to drive as the primary mode of travel – many of the alternative commute mode options which appear to be most competitive with driving alone still involve some form of driving. This includes driving to a Park-and-Ride facility in order to
take an express/commuter bus, and driving to a MARTA rail station in order to take a MARTA rail vehicle to the HQ.

This situation speaks to how prior transportation investments and land-use decisions can create a path dependency that restricts future changes. Some cities and regions may be car-dependent simply because driving alone has been perceived, encouraged and established as the most reliable way to travel. Conversely, more adventurous commuters who try alternative commute modes may end up being penalized for their efforts. This is especially true for commuters who live further away, as the likelihood of being forced to take a transit trip that needs transfers, runs indirect or meandering routes, or gets delayed by traffic, et cetera increases with distance. That said, for workers who live closer to their workplace, biking and/or walking may be doable options. Walking is of course slower than biking, but the latter may be unfamiliar to commuters and require initial attempts and encouragement before commuters are comfortable with biking to work.

Although this case study is unique to Metro Atlanta, GA and the specific employer, the study methodology is largely replicable and can be performed anywhere that has adequate GIS mapping and trip planner coverage, GTFS data, and locational data for trip origins. In addition, the major takeaways are largely transferable to employers in similar geographical and transportation landscapes. This analysis thus offers value to the field of employer TDM by providing a reference point for TDM practitioners. In conclusion, when it comes to providing and promoting alternative commute options, administrators of such programs must take care to ensure that employees are matched with mode choices which are as convenient as possible and to ensure that realistic expectations are maintained based on local conditions. For this purpose, feasibility analyses and evaluations such as this one may be conducted from time to time. As for certain
alternative commute modes which are found to be more inconvenient than others (e.g. local buses, as shown by this case study), TDM practitioners may have to advocate for improvements to service quality and infrastructure so that these options become more attractive.
# https://medium.com/analytics-vidhya/turn-right-in-2-miles-finding-distances-using-the-google-maps-api-and-pandas-fe8554f0b7d
# https://www.geeksforgeeks.org/python-calculate-distance-duration-two-places-using-google-distance-matrix-api/

# setup packages and API key

# ! pip install googlemaps # this if you're using the googlemaps package
# ! pip install pendulum
# ! pip install Jupyter-Beeper # https://pypi.org/project/Jupyter-Beeper/

# from googlemaps import Client as GoogleMaps # this if you're using the googlemaps package
import requests, json
import pandas as pd
import time
import pendulum
import jupyter_beeper

b = jupyter_beeper.Beeper()

api_key = XXXXXXXXXXXXXXXXXXXXXXXXXXX
print("Done!")

# reset current working directory

import os
path = os.getcwd()
print(path) # get current working directory

os.chdir(r"XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX"
path = os.getcwd()
print(path) # reset current working directory

#############################################################

addresses = pd.read_csv("XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX.csv")
addresses.head()

list = []
for ind in range(1,15):
    a = str('dep_time_') + str(ind)
    list.append(a)
a = str('drive_arr_time_') + str(ind)
list.append(a)
a = str('drive_dis_') + str(ind)
list.append(a)
a = str('drive_dur_') + str(ind)
list.append(a)
a = str('drive_dur_in_traffic_') + str(ind)
list.append(a)
a = str('drive_notes_') + str(ind)
list.append(a)

for l in list:
    addresses[l] = ""

# for morning commute via driving

for x in range(len(addresses)):
    time.sleep(1) #to add delay in case of large DFs
    print("Calculating for Entry", x+1 , "@", str(addresses['FULL ADDRESS'][x]))
    print()

    start = str(addresses['lat'][x]) + "," + str(addresses['long'][x])
    end = 'XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX' # EMPLOYER HQ COORDINATES

    # dt 1, driving
    print("Calculating... Driving @ DT1!")

    try:

        dt = 1614078000 # dt_1 = Tuesday, Feb 23, 2021 6:00:00 AM local time, according to https://www.epochconverter.com/

        url = 'https://maps.googleapis.com/maps/api/distancematrix/json?'
        url = str(url) + 'mode=driving' + '&origins=' + str(start) + '&destinations=' + str(end) + '
        &units=imperial' + '&traffic_model=pessimistic' + '&departure_time=' + str(dt) + '&key=' + str(api_key)
        r = requests.get(url)
        data = r.json()
        print(url)

        addresses['dep_time_1'][x] = str(pendulum.from_timestamp(dt))
        addresses['drive_arr_time_1'][x] = str(pendulum.from_timestamp((dt) +
        (data['rows'][0]['elements'][0]['duration']['value'])))
        addresses['drive_dis_1'][x] = data['rows'][0]['elements'][0]['distance']['text']

    except:
        pass
addresses['drive_dur_1'][x] = data['rows'][0]['elements'][0]['duration']['text']
addresses['drive_dur_in_traffic_1'][x] = data['rows'][0]['elements'][0]['duration_in_traffic']['text']

except Exception as e:
    addresses['drive_notes_1'][x] = "Unexpected error occurred."
    print("Unexpected error occurred.", e)
    b.beep()  # beep once for errors

# save results, reopen file
addresses.to_csv('testing_results.csv', index=False)
addresses = pd.read_csv("testing_results.csv")

# dt 2, driving
print("Calculating... Driving @ DT2!")

try:
    dt = 1614079800 #dt_2 = Tuesday, Feb 23, 2021 6:30:00 AM local time, according to https://www.epochconverter.com/

    url = 'https://maps.googleapis.com/maps/api/distancematrix/json?'
    url = str(url) + 'mode=driving' + '&origins=' + str(start) + '&destinations=' + str(end) + '&units=imperial' + '&traffic_model=pessimistic' + '&departure_time=' + str(dt) + '&key=' + str(api_key)
    r = requests.get(url)
    data = r.json()
    print(url)

    addresses['dep_time_2'][x] = str(pendulum.from_timestamp(dt))
    addresses['drive_arr_time_2'][x] = str(pendulum.from_timestamp((dt) + (data['rows'][0]['elements'][0]['duration']['value'])))
    addresses['drive_dis_2'][x] = data['rows'][0]['elements'][0]['distance']['text']
    addresses['drive_dur_2'][x] = data['rows'][0]['elements'][0]['duration']['text']
    addresses['drive_dur_in_traffic_2'][x] = data['rows'][0]['elements'][0]['duration_in_traffic']['text']

except Exception as e:
    addresses['drive_notes_2'][x] = "Unexpected error occurred."
    print("Unexpected error occurred.", e)
    b.beep()  # beep once for errors

# save results, reopen file
addresses.to_csv('testing_results.csv', index=False)
addresses = pd.read_csv("testing_results.csv")
# dt 3, driving
print("Calculating... Driving @ DT3!")

try:
    dt = 1614081600 # dt_3 = Tuesday, Feb 23, 2021 7:00:00 AM local time, according to https://www.epochconverter.com/

    url = 'https://maps.googleapis.com/maps/api/distancematrix/json?
    url = str(url) + 'mode=driving' + '&origins=' + str(start) + '&destinations=' + str(end) + '
    &units=imperial' + '&traffic_model=pessimistic' + '&departure_time=' + str(dt) + '&key=' + str(api_key)
    r = requests.get(url)
    data = r.json()
    print(url)
    addresses['dep_time_3'][x] = str(pendulum.from_timestamp(dt))
    addresses['drive_arr_time_3'][x] = str(pendulum.from_timestamp((dt) +
    (data['rows'][0]['elements'][0]['duration']['value'])))
    addresses['drive_dis_3'][x] = data['rows'][0]['elements'][0]['distance']['text']
    addresses['drive_dur_3'][x] = data['rows'][0]['elements'][0]['duration']['text']
    addresses['drive_dur_in_traffic_3'][x] =
    data['rows'][0]['elements'][0]['duration_in_traffic']['text']

except Exception as e:
    addresses['drive_notes_3'][x] = "Unexpected error occurred."
    print("Unexpected error occurred.", e )
    b.beep() # beep once for errors

# save results, reopen file
addresses.to_csv('testing_results.csv', index=False)
addresses = pd.read_csv("testing_results.csv")

# dt 4, driving
print("Calculating... Driving @ DT4!")

try:
    dt = 1614083400 # dt_4 = Tuesday, Feb 23, 2021 7:30:00 AM local time, according to https://www.epochconverter.com/

    url = 'https://maps.googleapis.com/maps/api/distancematrix/json?
    url = str(url) + 'mode=driving' + '&origins=' + str(start) + '&destinations=' + str(end) + '
    &units=imperial' + '&traffic_model=pessimistic' + '&departure_time=' + str(dt) + '&key=' + str(api_key)
    r = requests.get(url)
    data = r.json()
    print(url)
addresses['dep_time_4'][x] = str(pendulum.from_timestamp(dt))
addresses['drive_arr_time_4'][x] = str(pendulum.from_timestamp((dt) +
(data['rows'][0]['elements'][0]['duration']['value'])))
addresses['drive_dis_4'][x] = data['rows'][0]['elements'][0]['distance']['text']
addresses['drive_dur_4'][x] = data['rows'][0]['elements'][0]['duration']['text']
addresses['drive_dur_in_traffic_4'][x] =
data['rows'][0]['elements'][0]['duration_in_traffic']['text']

except Exception as e:
    addresses['drive_notes_4'][x] = "Unexpected error occurred."
    print("Unexpected error occurred.", e )
b.beep() # beep once for errors

# save results, reopen file
addresses.to_csv('testing_results.csv', index=False)
addresses = pd.read_csv("testing_results.csv")

#dt 5, driving
print("Calculating... Driving @ DT5!")

try:
    dt = 1614085200 #dt_5 = Tuesday, Feb 23, 2021 8:00:00 AM local time, according to
    https://www.epochconverter.com/

    url = 'https://maps.googleapis.com/maps/api/distancematrix/json?'
    url = str(url) + 'mode=driving' + '&origins=' + str(start) + '&destinations=' + str(end) +
    '&units=imperial' + '&traffic_model=pessimistic' + '&departure_time=' + str(dt) + '&key=' +
    str(api_key)
    r = requests.get(url)
    data = r.json()
    print(url)

    addresses['dep_time_5'][x] = str(pendulum.from_timestamp(dt))
    addresses['drive_arr_time_5'][x] = str(pendulum.from_timestamp((dt) +
    (data['rows'][0]['elements'][0]['duration']['value'])))
    addresses['drive_dis_5'][x] = data['rows'][0]['elements'][0]['distance']['text']
    addresses['drive_dur_5'][x] = data['rows'][0]['elements'][0]['duration']['text']
    addresses['drive_dur_in_traffic_5'][x] =
data['rows'][0]['elements'][0]['duration_in_traffic']['text']

except Exception as e:
    addresses['drive_notes_5'][x] = "Unexpected error occurred."
    print("Unexpected error occurred.", e )
b.beep() # beep once for errors
# save results, reopen file
addresses.to_csv('testing_results.csv', index=False)
addresses = pd.read_csv("testing_results.csv")

# dt 6, driving
print("Calculating... Driving @ DT6!")

# save results, reopen file
addresses.to_csv('testing_results.csv', index=False)
addresses = pd.read_csv("testing_results.csv")

print("...Calculated!")
print()

print ("All Done!")
# beep twice when done
time.sleep(2)
b.beep(frequency=600, secs=0.1, blocking=True)
time.sleep(1)
b.beep(frequency=600, secs=0.1, blocking=True)

# save results, reopen file
addresses.to_csv('testing_results.csv', index=False)
APPENDIX B – R CODE

rm(list = ls()) # do this to clear the global environment if necessary
gc() # frees up memory
dev.off() # removes plots from Plot window

# set working directory etc
getwd() # first see R's default location
setwd("XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX") # change directory address
getwd() # check that working directory is changed

#######
#######
#######

# specific packages for this exercise
install.packages("openxlsx")
install.packages("otpr")
install.packages("progress")
install.packages("beepr")

library("openxlsx")
library("otpr")
library("progress")
library("beepr")

?otp_get_times

#######
#######
#######

shortlist <- read.xlsx("XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX.xlsx")
head(shortlist)

total <- nrow(shortlist)# set number of records
pb <- progress_bar$new(total = total, format = "(:spin)[:bar]:percent")

for(i in 1:total) {
    pb$tick()# update progress bar

    trip <- otp_get_times(otpcon,
fromPlace = c(shortlist[i,]$lat, shortlist[i,]$long), #Employee address
toPlace = c(XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX), #Employer

HQ address
mode = "TRANSIT", detail = TRUE,
# arriveBy = TRUE,
date = "04-13-2021", time = "8:30:00",
maxWalkDistance = 1207.01, #SET THIS - 1609.34 is 1 mile, 1207.01 is 3/4 a mile, 804.67 is 1/2 a mile
minTransferTime = 1200, #SET THIS - 20 minutes for transfers
# detail = TRUE,
includeLegs = TRUE,
maxItineraries = 3)

# If response is OK update dataframe
if(trip$errorId == "OK") {shortlist[i, "c_status"] <- trip$errorId

#OPTION 1#
tryCatch(shortlist[i, "otp_tran_1_start"] <- trip$itineraries$start[1], error = function(e)
  {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_end"] <- trip$itineraries$end[1], error = function(e)
  {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_dur"] <- trip$itineraries$duration[1], error = function(e)
  {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_walkTime"] <- trip$itineraries$walkTime[1], error =
  function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_tranTime"] <- trip$itineraries$transitTime[1], error =
  function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_waitTime"] <- trip$itineraries$waitingTime[1], error =
  function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_transfer"] <- trip$itineraries$transfers[1], error = function(e)
  {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_1_mode"] <- trip$itineraries$legs[[1]]$mode[1], error =
  function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_1_depWait"] <-
  trip$itineraries$legs[[1]]$departureWait[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_1_dur"] <- trip$itineraries$legs[[1]]$duration[1], error =
  function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_1_dist"] <- trip$itineraries$legs[[1]]$distance[1], error =
  function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_1_routeName"] <-
  trip$itineraries$legs[[1]]$routeShortName[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_1_fromName"] <-
trip$itineraries$legs[[1]]$fromName[[1]], error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_fromLon"] <-
trip$itineraries$legs[[1]]$fromLon[[1]],
error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_fromLat"] <-
trip$itineraries$legs[[1]]$fromLat[[1]],
error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_toName"] <-
trip$itineraries$legs[[1]]$toName[[1]],
error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_toLon"] <-
trip$itineraries$legs[[1]]$toLon[[1]], error =
function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_toLat"] <-
trip$itineraries$legs[[1]]$toLat[[1]], error =
function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_mode"] <-
trip$itineraries$legs[[1]]$mode[[2]], error =
function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_depWait"] <-
trip$itineraries$legs[[1]]$departureWait[[2]], error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_dur"] <-
trip$itineraries$legs[[1]]$duration[[2]], error =
function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_dist"] <-
trip$itineraries$legs[[1]]$distance[[2]], error =
function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_1_routeName"] <-
trip$itineraries$legs[[1]]$routeShortName[[2]], error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_2_fromName"] <-
trip$itineraries$legs[[1]]$fromName[[2]], error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_2_fromLon"] <-
trip$itineraries$legs[[1]]$fromLon[[2]],
error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_2_fromLat"] <-
trip$itineraries$legs[[1]]$fromLat[[2]],
error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_2_toName"] <-
trip$itineraries$legs[[1]]$toName[[2]],
error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_2_toLon"] <-
trip$itineraries$legs[[1]]$toLon[[2]], error =
function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_2_toLat"] <-
trip$itineraries$legs[[1]]$toLat[[2]], error =
function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_2_mode"] <-
trip$itineraries$legs[[1]]$mode[[3]], error =
function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_2_depWait"] <-
trip$itineraries$legs[[1]]$departureWait[[3]], error = function(e) {print(paste("Skipped empty entry!")))
}
tryCatch(shortlist[i, "otp_tran_1_leg_3_dur"] <- trip$itineraries$legs[[1]]$duration[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_3_dist"] <- trip$itineraries$legs[[1]]$distance[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_3_routeName"] <- trip$itineraries$legs[[1]]$routeShortName[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_3_fromName"] <- trip$itineraries$legs[[1]]$fromName[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_3_fromLon"] <- trip$itineraries$legs[[1]]$fromLon[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_3_fromLat"] <- trip$itineraries$legs[[1]]$fromLat[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_3_toName"] <- trip$itineraries$legs[[1]]$toName[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_3_toLon"] <- trip$itineraries$legs[[1]]$toLon[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_3_toLat"] <- trip$itineraries$legs[[1]]$toLat[3], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_mode"] <- trip$itineraries$legs[[1]]$mode[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_depWait"] <- trip$itineraries$legs[[1]]$departureWait[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_dur"] <- trip$itineraries$legs[[1]]$duration[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_dist"] <- trip$itineraries$legs[[1]]$distance[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_routeName"] <- trip$itineraries$legs[[1]]$routeShortName[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_fromName"] <- trip$itineraries$legs[[1]]$fromName[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_fromLon"] <- trip$itineraries$legs[[1]]$fromLon[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_fromLat"] <- trip$itineraries$legs[[1]]$fromLat[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_toName"] <- trip$itineraries$legs[[1]]$toName[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_toLon"] <- trip$itineraries$legs[[1]]$toLon[4], error = function(e) {print(paste("Skipped empty entry!")))
    tryCatch(shortlist[i, "otp_tran_1_leg_4_toLat"] <- trip$itineraries$legs[[1]]$toLat[4], error = function(e) {print(paste("Skipped empty entry!"))}
tryCatch(shortlist[i, "otp_tran_1_leg_5_mode"] <- trip$itineraries$legs[[1]]$mode[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_depWait"] <- trip$itineraries$legs[[1]]$departureWait[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_dur"] <- trip$itineraries$legs[[1]]$duration[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_dist"] <- trip$itineraries$legs[[1]]$distance[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_routeName"] <- trip$itineraries$legs[[1]]$routeShortName[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_fromName"] <- trip$itineraries$legs[[1]]$fromName[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_fromLon"] <- trip$itineraries$legs[[1]]$fromLon[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_fromLat"] <- trip$itineraries$legs[[1]]$fromLat[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_toName"] <- trip$itineraries$legs[[1]]$toName[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_toLon"] <- trip$itineraries$legs[[1]]$toLon[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_5_toLat"] <- trip$itineraries$legs[[1]]$toLat[5], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_mode"] <- trip$itineraries$legs[[1]]$mode[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_depWait"] <- trip$itineraries$legs[[1]]$departureWait[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_dur"] <- trip$itineraries$legs[[1]]$duration[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_dist"] <- trip$itineraries$legs[[1]]$distance[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_routeName"] <- trip$itineraries$legs[[1]]$routeShortName[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_fromName"] <- trip$itineraries$legs[[1]]$fromName[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_fromLon"] <- trip$itineraries$legs[[1]]$fromLon[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_fromLat"] <- trip$itineraries$legs[[1]]$fromLat[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_toName"] <- trip$itineraries$legs[[1]]$toName[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_toLon"] <- trip$itineraries$legs[[1]]$toLon[6], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_6_toLat"] <- trip$itineraries$legs[[1]]$toLat[6], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_1_leg_7_mode"] <- trip$itineraries$legs[[1]]$mode[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_depWait"] <- trip$itineraries$legs[[1]]$departureWait[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_dur"] <- trip$itineraries$legs[[1]]$duration[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_dist"] <- trip$itineraries$legs[[1]]$distance[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_routeName"] <- trip$itineraries$legs[[1]]$routeShortName[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_fromName"] <- trip$itineraries$legs[[1]]$fromName[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_fromLon"] <- trip$itineraries$legs[[1]]$fromLon[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_fromLat"] <- trip$itineraries$legs[[1]]$fromLat[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_toName"] <- trip$itineraries$legs[[1]]$toName[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_toLon"] <- trip$itineraries$legs[[1]]$toLon[7], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_7_toLat"] <- trip$itineraries$legs[[1]]$toLat[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_1_leg_8_mode"] <- trip$itineraries$legs[[1]]$mode[8], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_8_depWait"] <- trip$itineraries$legs[[1]]$departureWait[8], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_8_dur"] <- trip$itineraries$legs[[1]]$duration[8], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_8_dist"] <- trip$itineraries$legs[[1]]$distance[8], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_8_routeName"] <- trip$itineraries$legs[[1]]$routeShortName[8], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_1_leg_8_fromName"] <-
trip$itineraries$legs[[1]]$fromName[8], error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_8_fromLon"] <- trip$itineraries$legs[[1]]$fromLon[8],
error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_8_fromLat"] <- trip$itineraries$legs[[1]]$fromLat[8],
error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_8_toName"] <- trip$itineraries$legs[[1]]$toName[8],
error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_8_toLon"] <- trip$itineraries$legs[[1]]$toLon[8], error =
function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_8_toLat"] <- trip$itineraries$legs[[1]]$toLat[8], error =
function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_mode"] <- trip$itineraries$legs[[1]]$mode[9], error =
function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_depWait"] <-
trip$itineraries$legs[[1]]$departureWait[9], error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_dur"] <- trip$itineraries$legs[[1]]$duration[9], error =
function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_dist"] <- trip$itineraries$legs[[1]]$distance[9], error =
function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_routeName"] <-
trip$itineraries$legs[[1]]$routeShortName[9], error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_fromName"] <-
trip$itineraries$legs[[1]]$fromName[9], error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_fromLon"] <- trip$itineraries$legs[[1]]$fromLon[9],
error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_fromLat"] <- trip$itineraries$legs[[1]]$fromLat[9],
error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_toName"] <- trip$itineraries$legs[[1]]$toName[9],
error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_toLon"] <- trip$itineraries$legs[[1]]$toLon[9], error =
function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_1_leg_9_toLat"] <- trip$itineraries$legs[[1]]$toLat[9], error =
function(e) {print(paste("Skipped empty entry!")))

#OPTION 2#

tryCatch(shortlist[i, "otp_tran_2_start"] <- trip$itineraries$start[2], error = function(e)
{print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_2_end"] <- trip$itineraries$end[2], error = function(e)
{print(paste("Skipped empty entry!")))}
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tryCatch(shortlist[i, "otp_tran_2_dur"] <- trip$itineraries$duration[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_walkTime"] <- trip$itineraries$walkTime[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_tranTime"] <- trip$itineraries$transitTime[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_waitTime"] <- trip$itineraries$waitingTime[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_transfer"] <- trip$itineraries$transfers[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_mode"] <- trip$itineraries$legs[[2]]$mode[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_deWait"] <- trip$itineraries$legs[[2]]$departureWait[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_dur"] <- trip$itineraries$legs[[2]]$duration[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_dist"] <- trip$itineraries$legs[[2]]$distance[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_routeName"] <- trip$itineraries$legs[[2]]$routeShortName[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_fromName"] <- trip$itineraries$legs[[2]]$fromName[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_fromLon"] <- trip$itineraries$legs[[2]]$fromLon[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_fromLat"] <- trip$itineraries$legs[[2]]$fromLat[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_toName"] <- trip$itineraries$legs[[2]]$toName[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_toLon"] <- trip$itineraries$legs[[2]]$toLon[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_1_toLat"] <- trip$itineraries$legs[[2]]$toLat[1], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_2_mode"] <- trip$itineraries$legs[[2]]$mode[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_2_deWait"] <- trip$itineraries$legs[[2]]$departureWait[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_2_dur"] <- trip$itineraries$legs[[2]]$duration[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_2_dist"] <- trip$itineraries$legs[[2]]$distance[2], error = function(e) {print(paste("Skipped empty entry!"))})```

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tryCatch(shortlist[i, "otp_tran_2_leg_2_routeName"] <-
trip$itineraries$legs[[2]]$routeShortName[2], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_2_fromName"] <-
trip$itineraries$legs[[2]]$fromName[2], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_2_fromLon"] <-
trip$itineraries$legs[[2]]$fromLon[2], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_2_fromLat"] <-
trip$itineraries$legs[[2]]$fromLat[2], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_2_toName"] <-
trip$itineraries$legs[[2]]$toName[2], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_2_toLon"] <-
trip$itineraries$legs[[2]]$toLon[2], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_2_toLat"] <-
trip$itineraries$legs[[2]]$toLat[2], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_mode"] <-
trip$itineraries$legs[[2]]$mode[3], error =
function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_depWait"] <-
trip$itineraries$legs[[2]]$departureWait[3], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_dur"] <-
trip$itineraries$legs[[2]]$duration[3], error =
function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_dist"] <-
trip$itineraries$legs[[2]]$distance[3], error =
function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_routeName"] <-
trip$itineraries$legs[[2]]$routeShortName[3], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_fromName"] <-
trip$itineraries$legs[[2]]$fromName[3], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_fromLon"] <-
trip$itineraries$legs[[2]]$fromLon[3], error =
function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_fromLat"] <-
trip$itineraries$legs[[2]]$fromLat[3], error =
function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_toName"] <-
trip$itineraries$legs[[2]]$toName[3], error =
function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_toLon"] <-
trip$itineraries$legs[[2]]$toLon[3], error =
function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_3_toLat"] <-
trip$itineraries$legs[[2]]$toLat[3], error =
function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_2_leg_4_mode"] <-
trip$itineraries$legs[[2]]$mode[4], error =
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_depWait"] <-
  trip$itineraries$legs[[2]]$departureWait[4], error = function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_dur"] <-
  trip$itineraries$legs[[2]]$duration[4], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_dist"] <-
  trip$itineraries$legs[[2]]$distance[4], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_routeName"] <-
  trip$itineraries$legs[[2]]$routeShortName[4], error = function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_fromName"] <-
  trip$itineraries$legs[[2]]$fromName[4], error = function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_fromLon"] <-
  trip$itineraries$legs[[2]]$fromLon[4], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_fromLat"] <-
  trip$itineraries$legs[[2]]$fromLat[4], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_toName"] <-
  trip$itineraries$legs[[2]]$toName[4], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_toLon"] <-
  trip$itineraries$legs[[2]]$toLon[4], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_4_toLat"] <-
  trip$itineraries$legs[[2]]$toLat[4], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_mode"] <-
  trip$itineraries$legs[[2]]$mode[5], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_depWait"] <-
  trip$itineraries$legs[[2]]$departureWait[5], error = function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_dur"] <-
  trip$itineraries$legs[[2]]$duration[5], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_dist"] <-
  trip$itineraries$legs[[2]]$distance[5], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_routeName"] <-
  trip$itineraries$legs[[2]]$routeShortName[5], error = function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_fromName"] <-
  trip$itineraries$legs[[2]]$fromName[5], error = function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_fromLon"] <-
  trip$itineraries$legs[[2]]$fromLon[5], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_fromLat"] <-
  trip$itineraries$legs[[2]]$fromLat[5], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_toName"] <-
  trip$itineraries$legs[[2]]$toName[5], error =
  function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_2_leg_5_toLon"] <- trip$itineraries$legs[[2]]$toLon[[5]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_5_toLat"] <- trip$itineraries$legs[[2]]$toLat[[5]], error = function(e) {print(paste("Skipped empty entry!")))

tryCatch(shortlist[i, "otp_tran_2_leg_6_mode"] <- trip$itineraries$legs[[2]]$mode[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_depWait"] <- trip$itineraries$legs[[2]]$departureWait[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_dur"] <- trip$itineraries$legs[[2]]$duration[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_dist"] <- trip$itineraries$legs[[2]]$distance[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_routeName"] <- trip$itineraries$legs[[2]]$routeShortName[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_fromName"] <- trip$itineraries$legs[[2]]$fromName[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_fromLon"] <- trip$itineraries$legs[[2]]$fromLon[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_fromLat"] <- trip$itineraries$legs[[2]]$fromLat[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_toName"] <- trip$itineraries$legs[[2]]$toName[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_toLon"] <- trip$itineraries$legs[[2]]$toLon[[6]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_6_toLat"] <- trip$itineraries$legs[[2]]$toLat[[6]], error = function(e) {print(paste("Skipped empty entry!")))

tryCatch(shortlist[i, "otp_tran_2_leg_7_mode"] <- trip$itineraries$legs[[2]]$mode[[7]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_depWait"] <- trip$itineraries$legs[[2]]$departureWait[[7]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_dur"] <- trip$itineraries$legs[[2]]$duration[[7]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_dist"] <- trip$itineraries$legs[[2]]$distance[[7]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_routeName"] <- trip$itineraries$legs[[2]]$routeShortName[[7]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_fromName"] <- trip$itineraries$legs[[2]]$fromName[[7]], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_fromLon"] <- trip$itineraries$legs[[2]]$fromLon[7], error = function(e) {print(paste("Skipped empty entry!")))}
tryCatch(shortlist[i, "otp_tran_2_leg_7_fromLat"] <- trip$itineraries$legs[[2]]$fromLat[7], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_toName"] <- trip$itineraries$legs[[2]]$toName[7], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_toLon"] <- trip$itineraries$legs[[2]]$toLon[7], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_7_toLat"] <- trip$itineraries$legs[[2]]$toLat[7], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_mode"] <- trip$itineraries$legs[[2]]$mode[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_depWait"] <- trip$itineraries$legs[[2]]$departureWait[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_dur"] <- trip$itineraries$legs[[2]]$duration[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_dist"] <- trip$itineraries$legs[[2]]$distance[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_routeName"] <- trip$itineraries$legs[[2]]$routeShortName[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_fromName"] <- trip$itineraries$legs[[2]]$fromName[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_fromLon"] <- trip$itineraries$legs[[2]]$fromLon[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_fromLat"] <- trip$itineraries$legs[[2]]$fromLat[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_toName"] <- trip$itineraries$legs[[2]]$toName[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_toLon"] <- trip$itineraries$legs[[2]]$toLon[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_8_toLat"] <- trip$itineraries$legs[[2]]$toLat[8], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_9_mode"] <- trip$itineraries$legs[[2]]$mode[9], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_9_depWait"] <- trip$itineraries$legs[[2]]$departureWait[9], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_9_dur"] <- trip$itineraries$legs[[2]]$duration[9], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_2_leg_9_dist"] <- trip$itineraries$legs[[2]]$distance[9], error = function(e) {print(paste("Skipped empty entry!")))

tryCatch(shortlist[i, "otp_tran_2_leg_9_routeName"] <-
  trip$itineraries$legs[[2]]$routeShortName[9], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
  tryCatch(shortlist[i, "otp_tran_2_leg_9_fromName"] <-
    trip$itineraries$legs[[2]]$fromName[9], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_2_leg_9_fromLon"] <-
    trip$itineraries$legs[[2]]$fromLon[9], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_2_leg_9_fromLat"] <-
    trip$itineraries$legs[[2]]$fromLat[9], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_2_leg_9_toName"] <-
    trip$itineraries$legs[[2]]$toName[9], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_2_leg_9_toLon"] <-
    trip$itineraries$legs[[2]]$toLon[9], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_2_leg_9_toLat"] <-
    trip$itineraries$legs[[2]]$toLat[9], error = function(e) {
      print(paste("Skipped empty entry!"))
    })

#OPTION 3#
tryCatch(shortlist[i, "otp_tran_3_start"] <-
  trip$itineraries$start[3], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
  tryCatch(shortlist[i, "otp_tran_3_end"] <-
    trip$itineraries$end[3], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_3_dur"] <-
    trip$itineraries$duration[3], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_3_walkTime"] <-
    trip$itineraries$walkTime[3], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_3_tranTime"] <-
    trip$itineraries$transitTime[3], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_3_waitTime"] <-
    trip$itineraries$waitingTime[3], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_3_transfer"] <-
    trip$itineraries$transfers[3], error = function(e) {
      print(paste("Skipped empty entry!"))
    })

tryCatch(shortlist[i, "otp_tran_3_leg_1_mode"] <-
  trip$itineraries$legs[[3]]$mode[1], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
  tryCatch(shortlist[i, "otp_tran_3_leg_1_depWait"] <-
    trip$itineraries$legs[[3]]$departureWait[1], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_3_leg_1_dur"] <-
    trip$itineraries$legs[[3]]$duration[1], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_3_leg_1_dist"] <-
    trip$itineraries$legs[[3]]$distance[1], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
  tryCatch(shortlist[i, "otp_tran_3_leg_1_routeName"] <-
    trip$itineraries$legs[[3]]$routeShortName[1], error = function(e) {
      print(paste("Skipped empty entry!"))
    })
tryCatch(shortlist[i, "otp_tran_3_leg_1_fromName"] <- 
trip$itineraries$legs[[3]]$fromName[1], error = function(e) {print(paste("Skipped empty entry!")))})
tryCatch(shortlist[i, "otp_tran_3_leg_1_fromLon"] <- trip$itineraries$legs[[3]]$fromLon[1], 
error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_1_fromLat"] <- trip$itineraries$legs[[3]]$fromLat[1], 
error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_1_toName"] <- trip$itineraries$legs[[3]]$toName[1], 
error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_1_toLon"] <- trip$itineraries$legs[[3]]$toLon[1], error = 
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_1_toLat"] <- trip$itineraries$legs[[3]]$toLat[1], error = 
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_mode"] <- trip$itineraries$legs[[3]]$mode[2], error = 
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_depWait"] <- trip$itineraries$legs[[3]]$departureWait[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_dur"] <- trip$itineraries$legs[[3]]$duration[2], error = 
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_dist"] <- trip$itineraries$legs[[3]]$distance[2], error = 
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_routeName"] <- 
trip$itineraries$legs[[3]]$routeShortName[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_fromName"] <- 
trip$itineraries$legs[[3]]$fromName[2], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_fromLon"] <- trip$itineraries$legs[[3]]$fromLon[2], 
error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_fromLat"] <- trip$itineraries$legs[[3]]$fromLat[2], 
error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_toName"] <- trip$itineraries$legs[[3]]$toName[2], 
error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_toLon"] <- trip$itineraries$legs[[3]]$toLon[2], error = 
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_2_toLat"] <- trip$itineraries$legs[[3]]$toLat[2], error = 
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_mode"] <- trip$itineraries$legs[[3]]$mode[3], error = 
function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_depWait"] <- 
trip$itineraries$legs[[3]]$departureWait[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_dur"] <- trip$itineraries$legs[[3]]$duration[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_dist"] <- trip$itineraries$legs[[3]]$distance[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_routeName"] <- trip$itineraries$legs[[3]]$routeShortName[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_fromName"] <- trip$itineraries$legs[[3]]$fromName[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_fromLon"] <- trip$itineraries$legs[[3]]$fromLon[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_fromLat"] <- trip$itineraries$legs[[3]]$fromLat[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_toName"] <- trip$itineraries$legs[[3]]$toName[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_toLon"] <- trip$itineraries$legs[[3]]$toLon[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_3_toLat"] <- trip$itineraries$legs[[3]]$toLat[3], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_mode"] <- trip$itineraries$legs[[3]]$mode[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_depWait"] <- trip$itineraries$legs[[3]]$departureWait[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_dur"] <- trip$itineraries$legs[[3]]$duration[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_dist"] <- trip$itineraries$legs[[3]]$distance[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_routeName"] <- trip$itineraries$legs[[3]]$routeShortName[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_fromName"] <- trip$itineraries$legs[[3]]$fromName[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_fromLon"] <- trip$itineraries$legs[[3]]$fromLon[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_fromLat"] <- trip$itineraries$legs[[3]]$fromLat[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_toName"] <- trip$itineraries$legs[[3]]$toName[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_toLon"] <- trip$itineraries$legs[[3]]$toLon[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_4_toLat"] <- trip$itineraries$legs[[3]]$toLat[4], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_5_mode"] <- trip$itineraries$legs[[3]]$mode[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_depWait"] <- trip$itineraries$legs[[3]]$departureWait[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_dur"] <- trip$itineraries$legs[[3]]$duration[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_dist"] <- trip$itineraries$legs[[3]]$distance[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_routeName"] <- trip$itineraries$legs[[3]]$routeShortName[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_fromName"] <- trip$itineraries$legs[[3]]$fromName[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_fromLon"] <- trip$itineraries$legs[[3]]$fromLon[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_fromLat"] <- trip$itineraries$legs[[3]]$fromLat[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_toName"] <- trip$itineraries$legs[[3]]$toName[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_toLon"] <- trip$itineraries$legs[[3]]$toLon[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_5_toLat"] <- trip$itineraries$legs[[3]]$toLat[5], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_6_mode"] <- trip$itineraries$legs[[3]]$mode[6], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_6_depWait"] <- trip$itineraries$legs[[3]]$departureWait[6], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_6_dur"] <- trip$itineraries$legs[[3]]$duration[6], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_6_dist"] <- trip$itineraries$legs[[3]]$distance[6], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_6_routeName"] <- trip$itineraries$legs[[3]]$routeShortName[6], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_6_fromName"] <- trip$itineraries$legs[[3]]$fromName[6], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_6_fromLon"] <- trip$itineraries$legs[[3]]$fromLon[6], error = function(e) {print(paste("Skipped empty entry!")))
  tryCatch(shortlist[i, "otp_tran_3_leg_6_fromLat"] <- trip$itineraries$legs[[3]]$fromLat[6], error = function(e) {print(paste("Skipped empty entry!")))
tryCatch(shortlist[i, "otp_tran_3_leg_6_toName"] <- trip$itineraries$legs[[3]]$toName[6], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_6_toLon"] <- trip$itineraries$legs[[3]]$toLon[6], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_6_toLat"] <- trip$itineraries$legs[[3]]$toLat[6], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_mode"] <- trip$itineraries$legs[[3]]$mode[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_depWait"] <- trip$itineraries$legs[[3]]$departureWait[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_dur"] <- trip$itineraries$legs[[3]]$duration[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_dist"] <- trip$itineraries$legs[[3]]$distance[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_routeName"] <- trip$itineraries$legs[[3]]$routeShortName[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_fromName"] <- trip$itineraries$legs[[3]]$fromName[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_fromLon"] <- trip$itineraries$legs[[3]]$fromLon[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_fromLat"] <- trip$itineraries$legs[[3]]$fromLat[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_toName"] <- trip$itineraries$legs[[3]]$toName[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_7_toLon"] <- trip$itineraries$legs[[3]]$toLon[7], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_8_mode"] <- trip$itineraries$legs[[3]]$mode[8], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_8_depWait"] <- trip$itineraries$legs[[3]]$departureWait[8], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_8_dur"] <- trip$itineraries$legs[[3]]$duration[8], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_8_dist"] <- trip$itineraries$legs[[3]]$distance[8], error = function(e) {print(paste("Skipped empty entry!"))})

tryCatch(shortlist[i, "otp_tran_3_leg_8_routeName"] <- trip$itineraries$legs[[3]]$routeShortName[8], error = function(e) {print(paste("Skipped empty entry!"))})
tryCatch(shortlist[i, "otp_tran_3_leg_8_fromName"] <-
  trip$itineraries$legs[[3]]$fromName[8], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_8_fromLon"] <-
  trip$itineraries$legs[[3]]$fromLon[8], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_8_fromLat"] <-
  trip$itineraries$legs[[3]]$fromLat[8], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_8_toName"] <-
  trip$itineraries$legs[[3]]$toName[8], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_8_toLon"] <-
  trip$itineraries$legs[[3]]$toLon[8], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_8_toLat"] <-
  trip$itineraries$legs[[3]]$toLat[8], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_9_mode"] <-
  trip$itineraries$legs[[3]]$mode[9], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_9_depWait"] <-
  trip$itineraries$legs[[3]]$departureWait[9], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_9_dur"] <-
  trip$itineraries$legs[[3]]$duration[9], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_9_dist"] <-
  trip$itineraries$legs[[3]]$distance[9], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
tryCatch(shortlist[i, "otp_tran_3_leg_9_routeName"] <-
  trip$itineraries$legs[[3]]$routeShortName[9], error = function(e) {
    print(paste("Skipped empty entry!"))
  })
write.xlsx(shortlist,
  "XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX.xlsx")
print(paste("Added new entry #", i, " to file!", sep = " "))
Sys.sleep(2)

} else {
# record error
shortlist[i, "c_status"] <- trip$errorId

print(paste("Error caught at entry #", i, "!", sep = " "))
# beep(sound = 7, expr = NULL)
Sys.sleep(2)}

}

write.xlsx(shortlist,
"XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX.xlsx")

Sys.sleep(3)
print("All done!")
# beep(sound = 8, expr = NULL)
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