AMERICAN UNIVERSITY OF BEIRUT

MODELING DEMAND FOR RIDESOURCING AS FEEDER FOR HIGH CAPACITY TRANSIT SERVICES: A CASE STUDY OF THE PLANNED BEIRUT BRT

by
NAJIB CHARBEL ZGHEIB

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AN ABSTRACT OF THE THESIS OF

Najib Charbel Zgheib for Master of Engineering
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Title: Modeling Demand for Ridesourcing as Feeder for High Capacity Transit Services: A Case Study of the Planned Beirut BRT

Ridesourcing (Uber, Careem, Lyft, …) is emerging as a main player in the transportation industry. However, its relation to mass transit remains ambiguous, with divided opinions on its complementarity or substitutive effect towards high capacity public transportation systems. This study examines the integration of ridesourcing and transit, particularly focusing on modeling the demand for mass transit when ridesourcing is used as an access or egress mode to mass transit. It extends the existing literature on the integration of transit and new mobility concepts by providing a modeling framework that incorporates all stages of multi-modal trips such as those that involve using mass transit. A mixed logit with error component structure is presented to capture correlations in unobserved factors across multi-modal alternatives sharing similar modes at certain stages. The framework incorporates uni-modal and multi-modal travel alternatives and distinguishes between access, main mode, and egress stages without applying constraints on possible combinations. An application to Beirut's planned Bus Rapid Transit (BRT) system, performed on a data set of 392 respondents, reveals that ridesourcing as a feeder mode is mostly popular with young commuters while also being perceived as more reliable than feeder buses and jitneys. Awareness and familiarity are major drivers for the service implying higher potential in the future. A complementarity effect with transit is found as the introduction of ridesourcing at the feeders' level is expected to drive an additional 2% of commuters to use the BRT. Decreasing ridesourcing fare is effective for its integration with transit, as a fare decrease of 50% increases BRT market share from 33.53% to 36.89% of all motorized trips, implying possible synergies between the two modes. Forecasting results further reveal that additional taxes on parking used by car commuters and increasing park and ride capacity at BRT stations are effective policies to augment BRT ridership.

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CHAPTER 1

INTRODUCTION

The aim of this thesis is to investigate the complementarity between new mobility concepts, notably ridesourcing (Uber, Lyft, Careem, …), and high capacity mass transit by developing a demand modeling framework for the new technology as first-mile-last-mile connection to transit stations. This chapter introduces the topic with section 1.1 stating the motivation behind the study. Section 1.2 describes some perceived relations between ridesourcing and other commute modes. Section 1.3 presents the research objectives and contribution, while section 1.4 provides the outline of the thesis.

1.1. Study Motivation

Mass transit systems have been at the heart of governmental spending on urban transportation for decades. They are built to enhance movement of people and goods, reduce dependency on automobiles, and diversify mobility options for all sectors of the community. Trends in public transportation ridership reflect increased popularity, despite some slowdown since 2014, as distance traveled in transit grew more than vehicle miles commuted on highways in the USA as shown in Figure 1 (APTA, 2019). This can be explained by a more developed transit infrastructure and an enhanced awareness on the benefits of public transportation. However, planners should look beyond main transit corridors as connectivity to major zones of trip origins and destinations is of paramount importance for efficient operations.

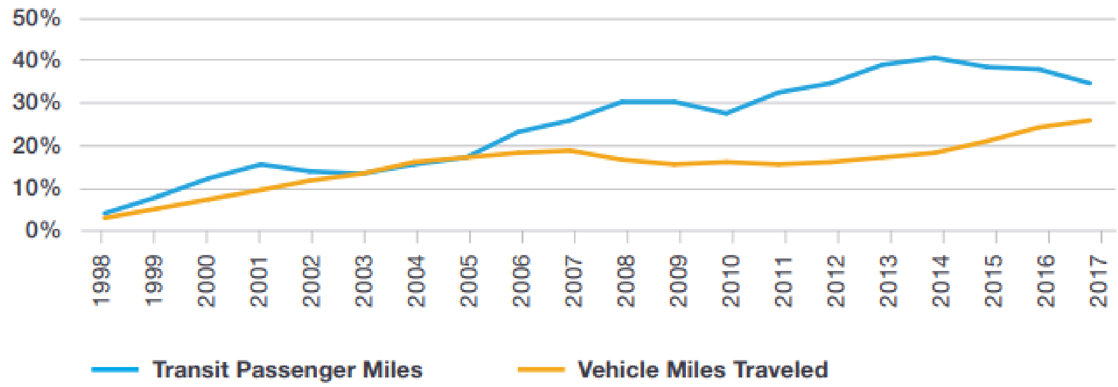

Figure 1: Growth in Transit Passenger Miles and Vehicle Miles Traveled in the USA with Respect to Levels at Year 1997 (APTA, 2019)

High capacity transit lines are mainly developed on dense corridors connecting hubs or within highly urbanized cities. Trip origins and destinations fall frequently beyond walking distance from public transportation stations. As a result, significant consideration should be attributed to planning first-mile and last-mile connections as they remain vital to the success of high capacity transit systems (Tabassum et al., 2017). In fact, accessibility to stations is one of the main factors affecting demand for transit, especially in developing countries where mobility options are limited or ineffective (Satiennam et al., 2006). It is not enough to develop transit corridors, but there is also need to look at integrated feeder networks that provide access and egress from transit stations.

Buses and jitneys are the most common form of motorized feeders. However, these modes mainly operate on fixed routes and their service frequency drops during off-peak hours. Consequently, alternate modes are being adopted to complement the deficiency of traditional feeders and enhance connectivity to transit stations. An example is bike sharing which is perceived as a sustainable solution to the last mile problem. Biking complements transit by extending reach beyond walking range and at lower costs than motorized feeders like neighborhood jitneys and buses (Pucher and Buehler, 2009). Moreover, non-motorized modes such as bikes and scooters reduce the environmental footprint of feeders and can be effective within cities where access and egress trips rarely extend beyond few kilometers. In spite of the numerous advantages, such feeder modes are by no means global solutions to the accessibility issue as they are susceptible to bad weather, difficult topography, availability and continuity of bike lanes, and coverage of transit stations. A case study in Beijing reveals that bike sharing stations did not cover all transit stops, a problem further aggravated by the lack of cooperation between different bike rental companies, which imposed wasted time and cost on users depositing bikes (Liu et al., 2012). When transit systems are built to serve beyond boundaries of a certain city, bike sharing is no longer feasible and the need becomes eminent for motorized feeders to connect origin and destination zones with public transport stations.

As a result, new mobility concepts could step up and establish their role in covering first-mile-last-mile connections. Ridesourcing, also known as ridehailing or transportation network companies (TNCs), is a notable example of such services. The new technology was not necessarily developed to feed transit but can fill this role due its flexible trip arrangement and wide service coverage. Ridesourcing is a mobile-based mobility platform (Uber, Careem, Lyft, …) that provides commuters with point-to-point rides through smartphone requests and incorporates tracking options, enhanced payment methods, and a review-based selection of drivers and vehicles with the aim of providing quality and unique experience to its users (Rayle et al., 2016). The service was introduced in 2009 and is already established in the transportation industry with diverse platforms reaching more cities and wider coverage.

Ridesourcing is already disrupting traditional travel modes in several cities. In the city of San Francisco, the pioneer in ridesourcing implementation, the service completes 170,000 trips on a typical weekday, which represents 15% in intra-city trips and is 12 times larger than taxi trips. The 570,000 vehicle miles of travel (VMT) commuted daily represent 20% of intra-San Francisco VMT (Castiglioni et al., 2017). Furthermore, 25% of the residents of the city use ridesourcing monthly, already exceeding the reach of taxis (SFMTA, 2014). Nowadays, Uber operates in 85 countries and covers over 903 cities according to UberEstimator, a tool that demarcates the company’s worldwide footprint (Uber, 2019). Trends reveal no signs of slowing down with significant year-to-year growth in number of rides and active users as shown in Figures 2 and 3. In 2019, Uber is estimated to provide 6.27 billion rides for its 110 million monthly active users worldwide (Statista, 2019).

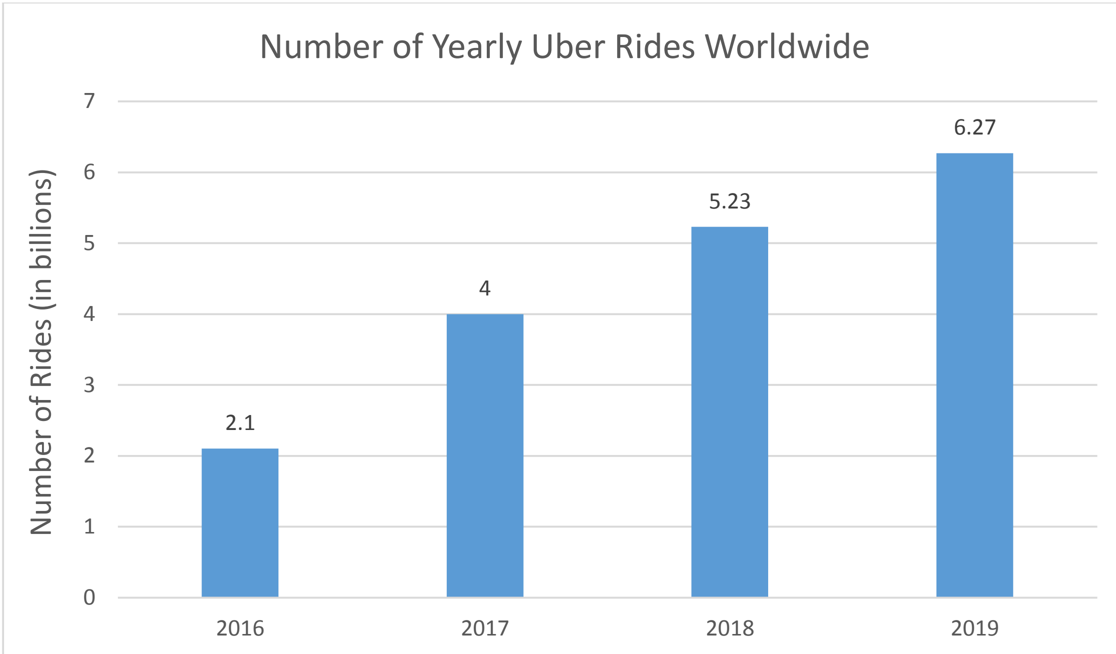

Figure 2: Number of Worldwide Uber Rides between 2016 and 2019 (Statista, 2019)

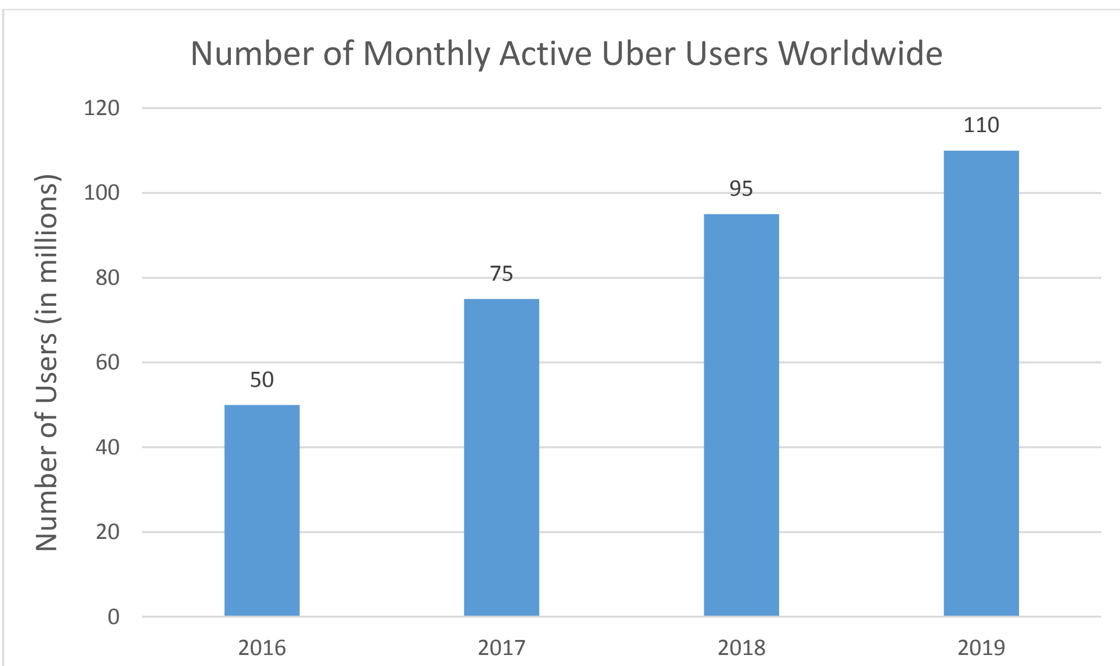

Figure 3: Number of Monthly Active Uber Users Worldwide between 2016 and 2019 (Statista, 2019)

Growth trends in the figures above further reveal that the total number of rides is increasing at a faster pace than the number of active users reflecting that not only the user base is getting wider, but the average number of trips per person is also growing. This is a sign of user satisfaction and of increased interest in the service after experiencing its advantages.

The increased popularity of ridesourcing is also affecting traditional travel modes. According to Lyft's 2019 economic impact report, 35% of Lyft users are non-car owners with 50% of them more likely to buy a car if the service did not exist (Lyft, 2019). Ridesourcing trips are expected to overcome bus trips in the United States by the end of 2018 and become the largest low capacity public transportation mode (Schaller, 2018). However, the factors affecting ridesourcing use and its impacts on travel behavior are still largely unexplored mainly due to lack of specific data, the uncertainty over the maturity of the service, and the divergence in conclusive results for different local contexts and user characteristics (Circella and Alemi, 2018). The growth of ridesourcing will also impact high capacity transit and feeder modes. A better understanding of the integration and interaction of ridesourcing with other transit modes is essential for future urban planning and focus should be placed on establishing the characteristics of new mobility concepts and the most suitable policies for a smooth and effective integration.

1.2. The Relation between Ridesourcing and Other Public Transport Modes

The exact impact of ridesourcing on other travel modes is still ambiguous. Some analysts conclude that the new technology will compete with public transport and attract customers from low capacity commute modes. A survey-based study in San Francisco reveals that 39% of ridesourcing users would have used taxis if the service was not available, while another 24% would have taken the bus (Rayle et al., 2014). This shows that the new service is competing for market share with other forms of public transport. Taxi companies seem to suffer the most with ridesourcing offering similar service while benefiting from several advantages such as the absence of car ownership and insurance costs. Licensing costs are also absent in several countries for ridesourcing which is not the case for taxis. Moreover, ridesourcing platforms allow their drivers to operate at their desired time or schedule which provides them with the flexibility to operate on part-time basis or during their free days only. This allows for more competitive pricing schemes and more appeal to drivers which enforces ridesourcing's position as an increasingly attractive substitute to traditional taxis (Hall and Krueger, 2017). UberX, which is the basic and least expensive Uber service, provides fare reductions in the order of 20% to 30% compared to traditional taxis (Greenwood and Wattal, 2017). This has caused regulatory challenges and raised calls for a reform in public policy to properly address the emerging service. Critics also claim that ridesourcing worsens congestion during peak periods, compromises public safety, and adopts controversial and blurred pricing algorithms (Rayle et al., 2014). A regression-based analysis of travel data in Las Vegas reveals that ridesourcing companies significantly cut the share of taxi trips in the city and affect them more than fixed route transit (Contreras and Paz, 2018). Accordingly, some cities banned ridesourcing companies, while others enforced regulations for their operation. For example, the city of Toronto passed a law in July 2016 to limit the number of ridesourcing vehicles, similar to the defined number of taxi license plates. The city also required ridesourcing drivers to acquire a special license and to meet driver screening and criminal background requirements before operating legally (Toronto, 2016).

On the other hand, proponents of the service suggest that it can complement transit and address some of its limitations. Ridesourcing enhances access for non-car owners and improves service during non-peak periods and evening hours (Cohen and Shaheen, 2018). In addition, it can extend the catchment area of mass transit by reaching beyond fixed route buses and serving areas where traditional modes are deficient. Improved first-mile-last-mile connections can lead to an increase in transit ridership and multi-modal trips which drives communities towards shared modes rather than private vehicle ownership. The integrated service can also reduce transport costs of users and drive economic activities around transit stations (Shaheen et al., 2015). Rayle et al. (2014) report that 4% of participants in their study used ridesourcing to reach or leave a public transport station, suggesting that the service is playing a role in first-mile-last-mile connections.

Several US cities are joining efforts with ridesourcing companies to provide first-mile-last-mile connections to transit stations. Subsidies on Uber trips were applied in some regions and the city of Centennial, Colorado teamed up with Lyft to provide free rides to and from light rail stations (Shen et al., 2017). Lyft is also developing a transit integration service called "Friends with Transit" consisting of shuttles that pool riders from their houses to mass transit stations and vice versa (Lyft, 2018). In fact, 29 partnerships were built between US cities and ridesourcing companies in an effort to improve mobility, reduce parking shortage, fill gaps in the transit system, and encourage smartphone planning for multi-modal trips combining shared rides with mass transit (Schwieterman et al., 2018). Figure 4 locates and briefly describes all 29 collaborations. The partnerships are motivated by several factors including better feeder connections, improved mobility for physically disabled users, an innovative image for the city, better coverage for low density regions, and serving late night travel needs. Another major motivation of such partnerships is the sharing of data which allows city planners to better understand travel patterns and impacts of ridesourcing, thus leading to better transit planning in the future (National Academies of Sciences, Engineering, and Medicine, 2019). The growth in partnerships between public authorities and ridesourcing companies implies a major need for studies that answer questions about the complementarity between this new mobility concept and high capacity mass transit systems.

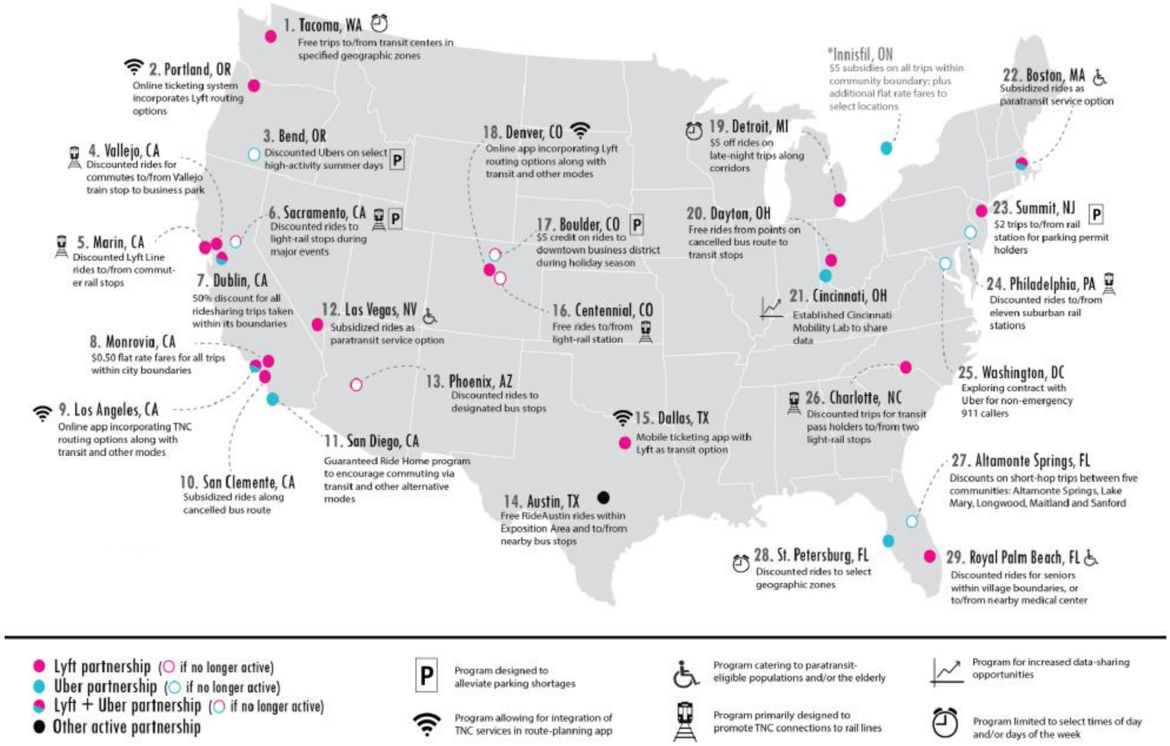

Figure 4: Partnerships between Ridesourcing Companies and Public Authorities in the United States (Schwieterman et al., 2018)

1.3. Research Objectives and Contribution

The increased popularity of ridesourcing and its establishment as a main commute mode in urban transportation imply a major contribution to feeder trips, which are prerequisite to effective transit operations. This study looks to investigate this issue and has the following main objectives:

- Understanding the effect of first-mile-last-mile connections, including ridesourcing, on transit ridership.
- Unveiling the main factors affecting demand for transit and feeder modes including ridesourcing.
- Providing a framework to model the overall transit trip without applying constraints on any of its three stages (access mode, main transport, and egress mode).
- Investigating the potential of ridesourcing as a feeder mode to high capacity mass transit in developing countries.

This research has both methodological and practical contributions. At a methodological level, we provide a demand modeling framework that incorporates all stages of a multi-modal trip simultaneously. Previous studies have tackled the first mile or last mile stages separately while fixing the other. The developed framework can also accommodate traditional or emerging commute modes beyond ridesourcing, whether as feeders to transit or to cover the entire trip. This allows for a flexible modeling of the choice between uni-modal or multi-modal trips, with all stages of the latter incorporated in the analysis.

At a practical level, the integration of emerging transportation technologies with transit is an emerging research topic that is tested in limited settings so far. The exact interactions between ridesourcing and transit are still ambiguous with studies leading to contradictory and inconclusive findings. This study contributes further towards unveiling the impact of the emerging technology on transit and tests its ability to improve first-mile-last-mile connections. The model is also used for policy analysis which provides planners and policy makers with better insights on the best strategies for an effective integration that does not negatively affect transit.

Moreover, the framework will be applied through a case study of the planned Beirut BRT which provides insights on the potential of ridesourcing in developing countries and draws comparisons with observed trends in developed urban cities. The topic of ridesourcing in developing countries, let alone its integration with transit, is rarely tackled in the literature. This research will analyze the prospect of ridesourcing in a context where traditional public transportation modes are deficient and badly perceived by a large portion of users, and where awareness about ridesourcing is also lower due to its recent introduction to the market.

The case study of the planned Beirut BRT will also provide local authorities with better understanding of the requirements for feeder networks which is lacking so far in the performed studies. The research will estimate the percentage of commuters that will shift from driving in different regions which helps in forecasting BRT ridership levels and traffic at various stations. Results will be forecasted under different policies which allows for better regulation and integration of the planned BRT system.

1.4. Thesis Organization

The thesis consists of six chapters, with chapter 1 being the introduction and the remaining chapters organized as follows:

- Chapter 2 provides a literature review on the first-mile-last-mile problem, as well as a review on the emergence of ridesourcing and its integration with transit.
- Chapter 3 describes the methodology adopted for modeling and the selection criteria used to select the model that best fits the data.

- Chapter 4 applies the modeling framework in the context of the planned Beirut BRT. The chapter includes a description of the study area, the designed survey, and the sampling plan and data collection. A descriptive analysis of the sample characteristics is also performed before developing a model specific to the case study.
- Chapter 5 presents the estimation results of the defined model and discusses insights and findings based on the model. Multiple policy scenarios are also defined to serve as decision tool for better implementation of the BRT and its feeders.
- Chapter 6 concludes the thesis and summarizes the main findings. It also reviews the contributions and limitations of the study, and provides the reader with directions for future research on this topic.

CHAPTER 2

LITERATURE REVIEW

This chapter provides a review of the literature on feeders to transit and ridesourcing. Section 2.1 gives a historical background on the first-mile-last-mile problem. Section 2.2 is an overview of ridesourcing and the factors affecting demand for the new service, in addition to its impacts on transit. Section 2.3 reviews the integration of ridesourcing with transit and presents the challenges and outcomes of this collaboration.

2.1. First-Mile-Last-Mile Connections to Transit

The first-mile-last-mile problem is a major topic in transportation planning and constitutes the focal point of diverse research projects. Sobeniak et al. (1979) developed disaggregate demand models for access modes to Canada's intercity transportation terminals. The study showed that socio-economic characteristics alongside travel costs, travel duration, and waiting time play a major role in the feeder selection process. Shared taxi rides are found to be more desirable as they maintain low travel cost and deliver the comfort and convenience of automobiles. A study developed on access trips to airports in the San Francisco Bay Area found that travelers are highly sensitive to access time, while trip purpose largely affects time and cost sensitivity (Harvey, 1986). Wen et al. (2012) developed a latent class nested logit model to explore access mode choice behavior for high-speed rail commuters in Taiwan. The analysis revealed that some commute modes share similar characteristics which induce correlation. As such, these should be grouped into nests to capture their resemblances. The study concluded that commuters are more sensitive to travel cost than travel time when it comes to the access stage of the trip and strategies should emphasize providing access modes at affordable rates.

Further studies evolved beyond one-dimensional choice sets to provide a wider representation of the choice process. Fan et al. (1993) built logit and nested logit models to analyze the selection process of access mode and transit station for commuter rail passengers in the Greater Toronto Area. Results showed that coefficients for in-vehicle travel time (IVTT) differ between drivers and passengers in an automobile in the access stage, and that out-of vehicle travel time (OVTT) outweighs in-vehicle travel time (IVTT) in implied disutility reflecting that transfer time and waiting time should be minimized for optimal service. Similarly, Debrezion et al. (2009) built a nested logit model to understand choice for both access mode and departure station for Dutch railway users. The study revealed that the nested logit model is suitable for the analysis and concluded that the infrastructure at stations, notably parking spaces and bike decks, enhance the attractiveness of the station, while public transport frequency and travel time govern mode choice.

Studies advanced later on to incorporate multiple stages of transit trips. In the Netherlands, multi-modal trips had a share of around 3% of total trips based on the 1996 Dutch National Travel Survey, and were growing compared to previous years. In relation to transit, multi-modal trips covered 80% of train trips and 20% of bus, tram and metro trips, which are modes more common for trips within cities and for shorter distances than train travel (Van Nes, 2002). Therefore, multi-modality is significant in the transport industry and is worthy of detailed investigation. Polydoropoulou and Ben-Akiva (2001) introduced a framework to model demand for different modes in a multi-modal trip. They designed a computer-based stated preference (SP) survey that includes choice experiments involving not only choice between private and public transport, but also choice of access mode when bus or transit is selected for main travel. The options provided for access were park and ride, kiss and ride, walking and bus (for transit only). Stated and revealed preference (RP) data were then combined in a nested logit model to assess choice behavior for main travel and access stage. The study concluded that combining RP and SP data is superior to estimation with separate data sets, and commuters' perception to transit delays plays a significant role in mode choice. Arentze and Moulin (2013) developed a demand model for multi-modal trips through a series of choice experiments. Three travel modes were considered: private car/bike, public transport (one mode for entire trip), and multi-modal trips. The study found that travel distance plays a major role in mode selection for multi-modal trips and the study distinguishes accordingly among three types of trips: short trips (5 km), medium trips (20 km), and long trips (65 km). Multi-modal trips become competitive as the trip length increases, and access and egress modes other than walking become more relevant. The study also revealed that sensitivity for tickets and parking fares is higher than that of fuel cost, and walking is preferred as access/egress mode when feasible. Hensher and Rose (2007) further revealed that total travel time should be split into different components such as in-vehicle travel time, waiting time, and walking time as each should be weighted differently for a better modeling of the decision process.

Several recent studies explored the potential of new mobility concepts as access modes for mass transit as these are expected to disrupt the transportation industry. Bike sharing was found to be helpful to transit as improved first-mile-last-mile connections lead to more reliance on public transportation and less on private cars, even though biking can replace transit trips for short intra-city trips (DeMaio, 2009). Yap et al. (2016) modeled demand for autonomous vehicles as egress mode to train trips in the Netherlands using stated preference techniques. The choice set included driving a private car or adopting a multi-modal train trip. For the latter, train is defined as the main travel mode with differentiation between 1st class and 2nd class travelers. The access mode was pre-defined and respondents had to select their preferred class for train travel and an egress mode out of the following: bus/tram/metro, bicycle, self-driven autonomous vehicle, and automatically driven autonomous vehicle. Results showed that the main potential for autonomous vehicles as last-mile transport is for first class travelers. These usually have higher incomes and value the luxury provided by autonomous vehicles such as direct and fast trips.

It must be noted that no studies were found where econometric models were developed to model both access and egress stages of the trip simultaneously based on stated preference data, particularly with respect to the consideration of new emerging modes like ridesourcing.

2.2. Ridesourcing

Before integrating ridesourcing with mass transit, it is essential to have a broad overview on the service and to understand its major drivers and impediments. Consent on the actual impacts of ridesourcing on the transport industry is not yet fully formed, but the topic has been a subject of interest recently and several related studies have been performed.

2.2.1. Factors Affecting Demand for Ridesourcing

Planning for ridesourcing relies primarily on identifying the main features affecting demand for the service. A California-based study (Alemi et al., 2018) investigated factors affecting the adoption of on-demand mobility by building binary logit models with and without attitudinal variables. Results from different models were consistent and revealed that young, well-educated individuals are most likely to use ridesourcing. The service was found to be popular with frequent plane travelers and commuters of long business trips, with mixed land use and enhanced regional accessibility also contributing to the utility of the service. On-demand mobility was also popular with technology oriented and pro-environmental groups. Analogous conclusions were found by Young and Farber (2019) as their study, based on survey data from the city of Toronto, also reflected more eagerness for ridesourcing among the younger generation, with higher interest amid wealthier segments.

Still investigating key drivers of on-demand mobility, Grahn et al. (2019) explored characteristics of the service users based on the United States' 2017 National Household Travel Survey. Beyond wealth, age, and education, the authors revealed that residence location and trip purpose significantly affect ridesourcing demand. Residents of urban areas used the service more frequently, especially for recreational trips, with larger city population and density increasing overall demand. The adoption rate in highly urbanized areas was double that of suburban regions in major US cities (Clewlow and Mishra, 2017). Similarly, Yu and Peng (2019) asserted that a relation exists between the built environment and demand for ridesourcing. Their study was based in Austin, Texas and concluded that a mixed land use with dense road networks, large population and employment, and transit accessibility induce higher demand for on-demand mobility services.

The likely high cost of a private ridesourcing ride was also addressed by ridesourcing companies through the introduction of ridesplitting (UberPool, Lyft Line, …), which is a form of on-demand mobility in which riders with compatible origins and destinations are matched in real time to the same driver and vehicle, allowing them to split the fee and reduce the commute cost (Shaheen et al., 2016). The new service makes ridesourcing more accessible to larger sectors of the community, allowing it to reach higher market share. Chen at al. (2017) took a deeper look at ridesplitting in the Chinese city of Hangzhou through data from DiDi Hitch, a platform matching passengers sharing similar routes, which is a leader in the Chinese ridesourcing market. Their study concluded that ridesplitting induces larger waiting times but is nonetheless attractive for long distance trips as it allows to reduce the associated travel costs.

2.2.2. Demand Modeling and Ridership Estimation

A few demand models for new mobility services can be found in the literature. Yang et al. (2009) modeled demand for diverse forms of shared mobility. Nine travel modes were available and divided into three categories: car-based modes, public transportation, and multi-modal trips. The respondent had to select one preferred travel mode from each category before making a final choice out of the three previously selected modes. Findings revealed that for car-related modes, higher parking costs and congestion charges are more deterring to commuters than general travel costs like fuel and ownership costs. Commuters departing during the morning peak were more sensitive to travel time than costs due to congestion and binding schedules. People with flexible departure time were also more likely to use car-related modes like driving, carpooling, or shared mobility.

El Zarwi et al. (2017) developed a framework to model and forecast adoption of new transport technologies like ridesourcing and autonomous vehicles. The presented model incorporated latent classes to study behavior towards technology adoption. Results showed that men and high income segments are more likely to be early adopters, and providing better coverage around technology firms will increase ridership as innovators are more likely to embrace the new mobility modes. Alemi et al. (2018) also built adoption models with latent constructs to capture heterogeneous preferences of commuters. Three classes were identified, with the first class corresponding to highly educated and independent individuals who are most likely to adopt ridesourcing and have a higher willingness to pay to reduce their travel time. The second class corresponded to dependent millennials who will hop on the new service in suitable settings such as mixed land use, long distance trips, and airport commutes. The third class consisted of older, less educated, and rural residents who are least likely to embrace the new mobility service.

Tarabay and Abou-Zeid (2019) investigated the potential of ridesourcing as a transport mode for social/recreational trips conducted by students of the American University Beirut, a private urban university located at the heart of the Lebanese capital. A choice model is developed based on revealed and stated preference data from a web-based survey and the study forecasts that around 22% of students will switch from their current modes to ridesourcing if well implemented. A 40% reduction in ridesourcing fare can lead to a switch proportion exceeding 30%.

2.2.3. Relation between Ridesourcing and Transit

As mentioned previously, the evidence on the relationship between ridesourcing and transit is mixed. Results from Young and Farber (2019) stated that the impact of ridesourcing on transit and other modes is too small to induce any clear positive or negative correlation, with taxi being the only exception as ridesourcing seems to be significantly cutting its market share. Similarly, Habib (2019) developed a model to investigate the competition of Uber with other commute modes and reached no clear evidence of competition between the service and private car, public transit, or non-motorized modes. However, with ridesourcing growing exponentially, it is expected to have an important effect on the ridership levels of other modes (Young and

Farber, 2019). Hence, it is essential to investigate further the relation of ridesourcing to transit and clearly define whether it is a relation of substitution or complementarity and under which conditions.

Strong claims are made about ridesourcing acting as a substitute to transit. While findings about the relation are mixed, studies lean towards the opinion that ridesourcing's substitutive effect outweighs its complementarity to transit (Tirachini, 2019). A sociodemographic investigation of ridesourcing users in Santiago de Chile concluded that the ratio of ridesourcing users who substitute ridesourcing with transit to those who combine both services is 11 to 1, reflecting a stronger substitutive effect (Tirachini and del Rio, 2019). Clewlow and Mishra (2017) established through a study of seven US metropolitan areas that ridesourcing is replacing 6% of bus trips and 3% of light-rail commutes reflecting a substitutive effect between on-demand mobility and transit. Substitutive effects were also reported by Lavieri et al. (2018) who built a model to assess demand generation and distribution of ridesourcing trips based on data from RideAustin, an Austin-based ridesourcing company. The model revealed that higher bus frequencies have a negative impact on weekday ridesourcing demand levels implying substitution patterns. Similar conclusions were reached by Graehler et al. (2019) who estimated that ridesourcing services induce a yearly decrease of 1.7% and 1.3% in heavy rail and bus ridership, respectively, in the United States. Hall et al. (2018) asserted that on-demand mobility complements transit in areas of low transit usage, but becomes a competitor in cities of high transit usage. This is mainly attributed to ridesourcing's ability to provide flexible and reliable trips in cities where transit level of service declines during peak hours due to capacity constraints.

On the other hand, opposing claims arise and back up the complementarity between ridesourcing and transit. Contreras and Paz (2018) suggested a complementary effect between the two commute modes in Las Vegas based on a linear regression analysis built on time-series travel dataset. Survey results from New Delhi revealed that 66% of respondents identified access to transit stations as a major reason to use ridesourcing (Ilavarasan et al., 2018). Grahn et al. (2019) reported that for similar sized US cities, ridesourcing usage tripled when heavy rail was available reflecting possible synergies. Hall et al. (2018) advanced this position by stating that ridesourcing ridership increased in London during hours of extended Underground service reflecting that the metro might have induced more demand for the service. The authors went further and performed a study on the impact of ridesourcing on mass transit based on a design that monitors difference-in-differences of transit ridership in US cities accounting for the time of entry of ridesourcing to the market and the intensity of the market entry. Results indicated that ridesourcing complements transit and increases its ridership by 5% two years after its introduction in a metropolitan urban area.

Ridesourcing can also play a role in solving the first-mile-last-mile problem by addressing limitations of existing feeders and encouraging multi-modality for access and egress trips (Shaheen and Chan, 2016). On-demand mobility can complement fixed alignment buses to extend the catchment area of transit. It can also replace costly low ridership buses that serve regions of low demand.

2.3. Integration of Ridesourcing and Transit

Research into the integration of ridesourcing with transit is still limited in the literature but has been gaining interest recently due to its potential in enhancing point-to-point connectivity and extending the reach of mass transit systems by covering first-mile and last-mile trip stages. Transit agencies and public authorities are increasing their efforts to successfully integrate ridesourcing schemes into their operations (Cane, 2017). Accordingly, several cities and transit agencies teamed up with ridesourcing companies to serve as feeders to transit, with enhanced mobility and data sharing being further motives for the collaboration (Schwieterman et al., 2018). However, the optimal logistics of such integration are yet to be fully uncovered.

Yan et al. (2019) tested this partnership by deriving a demand model for an integrated transit system at the University of Michigan Ann Arbor through combined revealed and stated preference data. The study investigated the potential of ridesourcing as feeder to university shuttles and found that the service can complement transit by extending its catchment area or by replacing buses on underutilized lines. Results showed that ridesourcing can give a significant boost to transit and also decreases operating costs by replacing low-ridership buses. Ridesourcing as last-mile transport reduces travel time and waiting time and focuses bus operations on high-density lines serving as a good complement to transit.

Shared mobility platforms are also combined with transit through Mobility-as-a-Service (MaaS) which aims to enhance movement within cities by building commute packages that combine public transit with private mobility providers (Polydoropoulou et al., 2019). Revenue allocation and fare splitting remain however a main issue. That is especially true for ridesourcing as it adopts dynamic pricing schemes rather than flat rates. Surge pricing is applied during peak hours and special events when demand levels soar. This surge is highly unpredictable and the lack of transparency about pricing schemes complicates the potential integration of ridesourcing with other mobility services (Jiao, 2018).

2.4. Gaps in the Literature

Studies that model demand for ridesourcing as feeder to transit are limited to the study by Yan et al. (2019) which is based in a university setting. The issue, to the author's knowledge, is not yet tackled in an urban or suburban context where the challenge of first-mile last-mile connectivity mainly lies. Moreover, most studies on ridesourcing are based on data from highly urbanized areas, with minor focus on suburban and rural regions. While demand is expected to be higher in urban settings, these only cover small areas where transit networks are usually dense, meaning that traditional feeders and non-motorized modes can provide connectivity to transit. Suburbs and rural areas are where transport coverage is limited and ridesourcing companies can fill the gap and provide first- and last-mile connections to mass transit systems.

In addition, ridesourcing characteristics are rarely investigated in developing countries that might not mirror the observed trends in developed urban cities. The factors behind demand for on-demand mobility are still vague and studies should be performed in different settings before reaching a universal consent and global understanding of the impacts of the new technology.

2.5. Summary of Research Studies on Ridesourcing

This section provides a summary table for studies involving demand models for ridesourcing and its relation with public transportation.

Table 1: Demand Modeling for Ridesourcing and its Relation to Transit: Summary of the Literature

Research Paper	Area	Type of Analysis	Significant Factors	Does it Involve First-Mile-Last-Mile?	Impact of Ridesourcing on Transit?
Alemi et al. (2018)	California, USA	Binary Logit Model	Age Education Attitude to Technology Land Use Mix Business Trips Airport Access	No	Substitute (minor effect)
Young and Farber (2019)	Toronto, Canada	Statistical Analysis of Survey Data	Age Income Car Ownership	No	No significant impact
Grahn et al. (2019)	USA	Generalized Linear Model	Income Age Education Trip Purpose Residence Area Population Density	No	No Clear Conclusion, Possible Complementarity
El Zarwi et al. (2019)	USA	Latent Class Choice Model (Multinomial Logit)	Gender Age Coverage around Tech Firms	No	Not Applicable
Yan et al. (2019)	University of Michigan Ann Arbor, USA	Mixed Logit Model	Additional Pick-ups Transfers Waiting Time	Yes	Complement (Replace low-usage bus lines, reduce operating costs)
Hall et al. (2018)	USA (metropolitan areas)	Linear Regression	Population Education	Yes	Complement
Lavieri et al. (2018)	Austin, USA	Multivariate Count Model, Fractional Split Model	Income Residential Density Activity Intensity Gender Car Ownership	No	Substitutive

Research Paper	Area	Type of Analysis	Significant Factors	Does it Involve First-Mile-Last-Mile?	Impact of Ridesourcing on Transit?
Clewlow and Mishra (2017)	USA (7 Major Cities)	Survey Analysis	Parking Availability Education Urban Settings Pop. Density	No	Not Applicable
Habib (2019)	Greater Toronto and Hamilton Areas	Constrained Multinomial Logit	Education Income Trip Start Time Pop. Density	No	No significant impact
Tirachini and del Rio (2019)	Santiago de Chile, Chile	Survey Analysis, Generalized Ordinal Logit Model	Trip Purpose Income Age Education	Yes	Substitutive Patterns Outweigh Complementary Effect

CHAPTER 3

RESEARCH METHODS

This chapter introduces the research methods and framework developed for demand modeling of a mass transit system with integrated ridesourcing for the feeder stages. Section 3.1 presents the modeling framework and formulation, while section 3.2 discusses the procedure of selecting the most suitable model based on multiple criteria. Section 3.3 discusses the data required for model estimation based on the proposed framework, and section 3.4 covers policy analysis.

3.1. Modeling Scheme

This section defines the proposed modeling approach by providing a framework for the modeling process as well as the model formulation.

3.1.1. Modeling Framework

The demand modeling procedure of this research requires data collection through means of a survey involving stated preferences (SP) and/or revealed (RP) preferences of respondents. The problem at hand involves selecting between uni-modal trips and multi-modal transit trips with the latter requiring the choice of all modes involved in the trip. As such, some alternatives share common access modes, egress modes, and/or main modes. A multinomial mixed logit model with error components is thus proposed as it captures the correlation in unobserved factors across alternatives. Level-of-service variables (travel time and cost components) of different travel alternatives and the actual choice of respondents can be provided by either SP or RP data. Socio-economic characteristics of respondents, actual travel behavior, and perceptions towards different commute modes are collected through means of RP data. The modeling framework that incorporates both RP and SP data is illustrated in Figure 5.

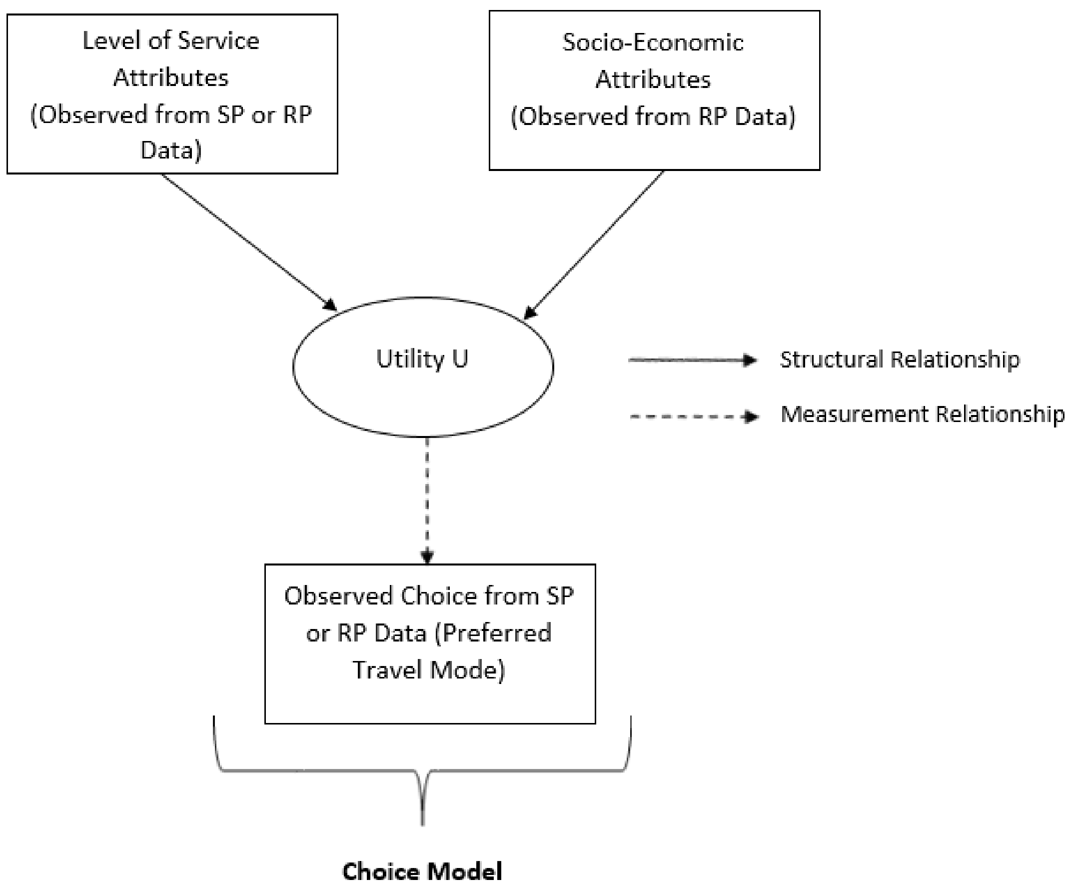

Figure 5: Modeling Framework

3.1.2. Background on Discrete Choice Models

Behavioral models have been long adopted to explain how agents act when they face a choice. When the choice is discrete, such as the selection of a preferred travel mode, discrete choice analysis is employed to build behavioral process equations that can predict the agent's choice given the variables of interest (Train, 2009). A typical discrete choice problem should address four main elements: the decision maker, the alternatives, the attributes, and the decision rule. Discrete choice models are disaggregate and the decision maker is the individual of concern. The alternatives are represented by a choice set containing a finite number of options that are available to the decision maker. The attributes are variables that measure the benefits and costs of the alternatives to the decision maker, while the decision rule is the process based on which alternatives are compared and ranked (Ben-Akiva and Bierlaire, 1999). The most common rule to model behavior for cases with discrete outcomes is random utility maximization. That is, each alternative is associated with a utility function and the decision maker is assumed to select the alternative that yields the highest utility (Ben-Akiva and Lerman, 1985).

The utility function is based on factors that are observed by the analyst, and others that are not observed. Unobserved factors reflect limitations in the analyst's data collection tools and his/her inability to capture all features behind the selection process, in addition to taste heterogeneity. They are represented by a random disturbance term that cannot be deterministically quantified. Accordingly, the decision maker's choice becomes probabilistic and the probability density function of the disturbance term defines the resulting modeling family (Train, 2009).

The logit model is the most commonly used discrete choice model which assumes that disturbances follow an Extreme Value Type I distribution and are independent and identically distributed across alternatives and individuals (Train, 2009). The mixed logit is a highly flexible extension of the logit family that addresses three limitations of the logit by allowing for correlation among unobserved factors of different utility functions, random taste variation with heterogeneous sensitivities across individuals, and unrestricted substitution patterns (McFadden and Train, 2000). The mixed logit will be adopted for the purpose of this research with error components added to utility functions to capture correlation among unobserved factors of different alternatives.

3.1.3. Model Formulation: Multinomial Mixed Logit Model with Error Components

This section covers the modeling structure and formulation that are proposed for the problem at hand including the definition of utility functions and the derivation of the likelihood function.

3.1.2.1. The Choice Model

The choice model defines the utilities of all possible travel mode combinations as a function of observed level-of-service attributes of the trip, socio-economic characteristics of the decision maker, and unobserved error components and disturbance terms. First, let J be the set of all alternatives with $j \in J$ the index of any particular one. The utility of alternative *j* is structured as shown in equation (1):

$$U_{j,n,t} = V_{j,n,t} + \omega_{j,n} + \varepsilon_{j,n,t} \tag{1}$$

Every alternative *j* incorporates a mode of main transport *m*, in addition to an access mode *a* and egress mode *e* when needed to complete the door-to-door trip. $V_{j,n,t}$ is the systematic utility of alternative j for individual n in scenario t (assuming the availability of panel data through a stated preferences survey for example) and is expressed as follows:

$$V_{j,n,t} = \sum_{m=1}^{M} I_m^{Main,j} V_{m,n,t}^{Main} + \sum_{a=1}^{A} I_a^{Acc,j} V_{a,n,t}^{Acc} + \sum_{e=1}^{E} I_e^{Egr,j} V_{e,n,t}^{Egr}$$

$$\forall \mathrm{j} \in \mathrm{J}, m \in M, a \in \mathrm{A}, and\ e \in \mathrm{E} \tag{2}$$

Where $V_{m,n,t}^{Main}$ is the systematic utility component specific to main mode m, $V_{a,n,t}^{Acc}$ is the systematic utility component specific to access mode a, and $V_{e,n,t}^{Egr}$ is the systematic utility component specific to egress mode e, and:

$$I_m^{Main,j} = \begin{cases} 1 & if\ alternative\ j\ includes\ mode\ m\ as\ main\ mode\ of\ transport \\ 0 & otherwise \end{cases} \tag{3}$$

$$I_a^{Acc,j} = \begin{cases} 1 & if\ alternative\ j\ includes\ mode\ a\ as\ access\ mode \\ 0 & otherwise \end{cases} \tag{4}$$

$$I_e^{Egr,j} = \begin{cases} 1 & if\ alternative\ j\ includes\ mode\ e\ as\ egress\ mode \\ 0 & otherwise \end{cases} \tag{5}$$

M is the set of available main travel modes, and A and E are the sets of access and egress modes available, respectively, for multi-modal trips. Multi-modal trips are defined to have a main transport mode operating on a fixed alignment, mainly the case for high capacity mass transit systems, which requires access and egress modes to complete the door-to-door trip.

$\sum_{m=1}^{M} I_m^{Main,j}$ is strictly 1 as each trip must have exactly one main travel mode. $\sum_{a=1}^{A} I_a^{Acc,j} \& \sum_{e=1}^{E} I_e^{Egr,j}$ can be either 0 for uni-modal trips, or 1 for multi-modal trips assuming that only one access and one egress modes are sufficient to connect commuters from/to transit stations.

The systematic utilities of different trip stages are defined as follows:

$$V_{a,n,t}^{Acc} = \alpha_a^{Acc} + \beta X_{a,n,t}^{Acc} \qquad a \in A \tag{6}$$

$$V_{m,n,t}^{Main} = \alpha_m^{Main} + \beta X_{m,n,t}^{Main} \qquad m \in M \tag{7}$$

$$V_{e,n,t}^{Egr} = \alpha_e^{Egr} + \beta X_{e,n,t}^{Egr} \qquad e \in E \tag{8}$$

X is a vector of exogenous level-of-service variables (travel time and cost components) specific to each stage, in addition to the socio-economic characteristics of the respondent. β is a vector of coefficients some of which are fixed across individuals (β_n^f is the vector of all fixed coefficients), while others can be random to model random taste variations (up to K_r random parameters, with the k^{th} random parameter denoted as $\beta_{k,n}^r$). V includes a constant α that is specific to a mode or stage of the trip, with one out of all constants normalized to zero. This approach reduces the number of constants to be estimated as constants are specific to each mode rather than each alternative, where an alternative is a combination of an access mode – main mode – egress mode (such as in the approach adopted in Ben-Akiva and Abou-Zeid, 2013).

$\omega_{j,n}$ is a random time-invariant component that is specific to alternative j and individual n and is expressed as follows:

$$\omega_{j,n} = \sum_{m=1}^{M} I_m^{Main,j} \omega_{m,n}^{Main} + \sum_{a=1}^{A} I_a^{Acc,j} \omega_{a,n}^{Acc} + \sum_{e=1}^{E} I_e^{Egr,j} \omega_{e,n}^{Egr} \tag{9}$$

Where $\omega_{m,n}^{Main}$, $\omega_{a,n}^{Acc}$, and $\omega_{e,n}^{Egr}$ are error components specific to main mode m, access mode a, and egress mode e, respectively. Each error component has a normal distribution with 0 mean and standard deviation to be estimated. $\varepsilon_{j,n,t}$ is an Extreme Value Type I distribution with zero mean and variance normalized to $\pi^2/6$ to set the scale of the utility of alternative j in scenario t.

It must be noted that for simplicity this framework assumes that every multi-modal trip has uni-modal access and egress stages. In reality, multiple modes can be used for the access or egress trips. Moreover, a multi-modal trip might only include an access stage without an egress stage when the final destination is located at the drop-off location of the main travel mode, and vice versa. The framework can be expanded to account for such cases by relaxing the constraints on $\sum_{a=1}^{A} I_a^{Acc,j}$ *and* $\sum_{e=1}^{E} I_e^{Egr,j}$ and allowing them to exceed 1 when multiple modes are used for access or egress, or allow one of them to be 0 when access or egress trips are not necessary. However, this is not required for this thesis and the simplified utility defined in equation (2) will be adopted.

3.1.2.2. The Likelihood Function

The method of maximum likelihood is used to estimate the model. In this section, the likelihood function that needs to be maximized in model estimation is expressed. Let Y_n be a $J \times T$ matrix reflecting the choice of individual *n* across all presented scenarios T. $y_{j,n,t}$ is a binary choice indicator that defines elements of the Y_n matrix as follows:

$$y_{j,n,t} = \begin{cases} 1 & \textit{if alternative } j \textit{ is selected by individual } n \textit{ in scenario } t \\ 0 & \textit{otherwise} \end{cases} \quad (10)$$

The likelihood of observing all the choices of individual *n* can be expressed as follows:

$$P(Y_n|X_n, \beta_n^f, \vec{\lambda}) = \int_{\omega_M^{Main}} \dots \int_{\omega_1^{Main}} \int_{\omega_A^{Acc}} \dots \int_{\omega_1^{Acc}} \int_{\omega_E^{Egr}} \dots \int_{\omega_1^{Egr}} \int_{\beta_{K_r}^r} \dots \int_{\beta_1^r}$$

$$\left[\prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{e^{V_{j,n,t}+\omega_{j,n}}}{\sum_{p=1}^{J} e^{V_{p,n,t}+\omega_{p,n}}}\right)^{y_{j,n,t}}\right] \prod_{m=1}^{M} f(\omega_{m,n}^{Main}) \prod_{a=1}^{A} f\left(\omega_{a,n}^{Acc}\right) \prod_{e=1}^{E} f\left(\omega_{e,n}^{Egr}\right) \prod_{k=1}^{K_r} f(\beta_{k,n}^r) \tag{11}$$

$$d\omega_1^{Main} \dots d\omega_M^{Main}\, d\omega_1^{Acc} \dots d\omega_A^{Acc}\, d\omega_1^{Egr} \dots d\omega_E^{Egr}\, d\beta_1^r \dots d\beta_{K_r}^r$$

Where $f(.)$ is the probability density function of the corresponding error component or parameter. $\vec{\lambda}$ is a vector including all parameters that define the distributions of the random terms.

The likelihood function is the probability of observing the choices of all respondents in the final sample and can be expressed as:

$$L = \prod_{n=1}^{N} P(Y_n|X_n, \beta_n^f, \vec{\lambda}) \tag{12}$$

The log-likelihood becomes the following:

$$LL = \sum_{n=1}^{N} \ln\left[P(Y_n|X_n, \beta_n^f, \vec{\lambda})\right] \tag{13}$$

3.2. Selection Criteria

This section presents the model selection procedure which is based on a number of considerations including the sign of the estimated coefficients, the statistical significance of the variables, the goodness of fit of the models, the resulting value of time, and cross validation prediction tests.

3.2.1. Sign of Estimated Coefficients and Significance of Variables

The estimated coefficients quantify the effect of each variable on the utility of the alternatives that incorporate it, and thus on the overall selection process. A significant coefficient implies that the corresponding variable is integral to the utility of the equivalent mode and its effect is non-zero at the adopted confidence level. As for the sign, it reflects whether the variable improves or deteriorates the utility of corresponding alternatives. For example, an increment in travel time for the same trip adds more burden on the commuter which implies a negative coefficient for the travel time coefficient. The relative magnitude of different coefficients also provides insights on the comparative effect of different variables on the utility of different travel modes.

3.2.2. Goodness of Fit

Goodness of fit measures are widely used in model selection. In discrete choice models, the final log-likelihood $LL_{(\hat{\beta})}$ which was discussed earlier is the main factor for model adoption, with a higher $LL_{(\hat{\beta})}$ implying better model fit. Another important criterion is the ρ^2 measure which also reflects how well the model fits the data and is computed as follows:

$$\rho^2 = 1 - \frac{LL_{(\hat{\beta})}}{LL_0} \tag{14}$$

Where LL_0 represents the log-likelihood of the null model where all parameters are zero (Johansen, 2013). ρ^2 ranges between 0 and 1. A higher ρ^2 indicates a model that fits the data better.

A high ρ^2 might sometimes reflect an over-fitted model when the number of parameters is very high. The Akaike Information Criteria (AIC) and the Bayesian Information Criterion (BIC) address this limitation by penalizing the excess of parameters in a model. Equations (15) and (16) provide the formulas for the AIC and BIC measures, respectively.

$$AIC = -2LL_{(\hat{\beta})} + 2K \tag{15}$$

$$BIC = -2LL_{(\hat{\beta})} + 2\log(N)K \tag{16}$$

Where $LL_{(\hat{\beta})}$ is the final log-likelihood of the estimated model, *K* is the number of parameters in the model, and *N* is the sample size. The actual value of the criterion is meaningless but relative values can be used to compare multiple models. The best fitting model is the one with the lowest AIC/BIC criterion.

It must be noted that all criteria in this section can only be used to compare models estimated with the same data set and using the same dependent variable.

3.2.3. Value of Time Analysis

The value of time (VOT) is a key concept in transport planning as it allocates a monetary value to the travel time savings induced by new infrastructure projects or transport services based on the tradeoff between travel time and cost (Ben-Akiva and Lerman, 1985). The VOT is the marginal utility of travel time divided by the marginal utility of travel cost. A deterministic VOT is obtained when both parameters are fixed, while a probabilistic distribution is defined through Monte Carlo simulation when one or both parameters are random. The VOT will be computed for different trip stages and compared to the typical values found in the literature.

3.2.4. Cross Validation Prediction Test

K-folds cross validation tests are applied to evaluate the robustness of estimation and predictive power of the obtained models. The test consists of splitting the data set into *k* equal sub-sets that are mutually exclusive and collectively exhaustive. In these tests, *k* -1 sub-sets are used for model estimation before applying it on the remaining sub-set to compute the likelihood of replicating the observed choices. The prediction test is repeated over all possible combinations of sub-sets and the likelihood of all combinations is summed to obtain the overall final likelihood of the proposed model. The number of folds can vary from 2 to N, where N is the sample size, in which case the test is named leave-one-out cross validation as N-1 data points are used for estimation before applying the model to find the likelihood of observing the choices of the remaining data point. Kohavi (1995) suggests that no more than 10 folds should be used for cross validation even when computational power allows for it. In this research, a 5-fold cross validation will be performed to compare models.

3.3. Data Needs

This section covers data that needs to be collected for the proposed modeling framework. The needed data is obtained using a commuter survey and can be separated into the following categories:

1. Trip characteristics of the individual including origin, destination, mode of commute, time of departure, and travel costs.
2. Socio-economic characteristics of the respondent including gender, income, age, education, household size, and car ownership.
3. Revealed preferences towards existing travel modes including travel trends, frequency of use of existing commute modes especially public transportation, and familiarity with emerging mobility services that are of concern in the study.
4. Stated preference data which reveals the choices made by the decision maker when provided with multiple hypothetical scenarios. The choice set should cover all modes of main transport alongside access and egress modes for mass transit that are of interest in the study. The stated preference design should also provide a flexible and clear experiment in addition to all level-of-service attributes that are judged to be pivotal in the selection process.
5. Attitudinal indicators and perceptions of the users should be collected when latent variables are to be included in the model. In that case, respondents are provided with numerous statements and are then asked to report their level of agreement on a 5-point or 7-point scale.

3.4. Policy Analysis

The final selected model will also be used for forecasting under different policy scenarios to give an estimate of the demand for ridesourcing at the feeder stage in addition to its impact on overall transit ridership. Policies will cover pricing schemes of ridesourcing and other modes in addition to operational policies and will be tested by inducing changes in the variables of interest and forecasting the corresponding results which will be compared to a base scenario.

The sample enumeration method will be used to measure the impact of the proposed policies. These policies serve as a tool for planners and policy makers aiming for a better integration of ridesourcing with mass transit and looking to effectively provide enhanced first-mile-last-mile coverage.

CHAPTER 4
|
CASE STUDY: DEMAND MODELING FOR RIDESOURCING AS FEEDER TO THE PLANNED BEIRUT BRT

This chapter applies the proposed modeling framework in the context of a case study of the planned Beirut Bus Rapid Transit (BRT). The model outputs can be used to give a better overview of the potential of integrating ridesourcing with transit. Section 4.1 describes the transportation sector in Lebanon and the characteristics of the planned Beirut BRT. Section 4.2 delineates the study area. Sections 4.3 and 4.4 present the survey deign and data collection procedure, respectively, before providing the descriptive analysis of the sample in section 4.5. Finally, section 4.6 presents the model specific to the case study with different approaches considered.

4.1. Transportation Context in Lebanon and the Planned Beirut BRT

4.1.1. Overview of the Transportation Sector in Lebanon

Lebanon suffers from a growing traffic congestion problem, especially in its capital city Beirut and its suburbs. This is due to increasing travel demand and insufficient road capacity to cater for diverse activities of the population at an acceptable level of service. As a result, commuters entering the Lebanese capital experience excessive delays that extend beyond peak hours. The northern entrance to Beirut suffers the most from congestion as it handles more than 50% of traffic entering the capital, which translates to over 300,000 vehicles entering on a daily basis. The resulting congestion imposes extended delays and a 20-km trip from Jounieh to Beirut can take over 90 min (CDR/World Bank, 2017) at peak hours.

Part of this severe congestion can be attributed to high car dependency and agglomeration of jobs and services in the capital. The private automobile is responsible for over 80% of motorized trips conducted in Greater Beirut Area (GBA) during the AM peak, a share that is even larger outside GBA where public transportation is more deficient (IBI Group and TEAM International, 2009). Car ownership in Lebanon is of the order of 1 car per 3 persons, with an average occupancy of 1.2 persons per vehicle (MoE/UNDP/GEF, 2015). High capacity transit systems that operate on fixed alignments with their own right of way are absent, and non-motorized modes are scarce due to the lack of suitable infrastructure such as sidewalks and dedicated bike lanes. Cars keep dominating despite low fares of jitneys and buses due to reliability concerns and bad perception by the public (Danaf et al., 2014). The total share of public transportation in the GBA is around 29% distributed mainly over jitneys/taxis which account for 19% of total travel and buses/vans that serve 10% of overall travel (Kaysi et al., 2010).

4.1.2. The Planned Beirut BRT

One approach towards mitigating congestion is to develop a high capacity mass transit system that provides an alternative to private cars. Bus Rapid Transit (BRT) constitutes an example of such systems that is widely popular in developing countries. The system is a bus-based public transit scheme that dedicates lanes for bus operations to avoid interaction with regular traffic, with priority at intersections to reduce delays. Istanbul implemented a BRT system in 2007 based on the system's ability to match the service level of rail systems while maintaining the flexibility of buses at relatively lower investment costs (Babalik-Sutcliffe et al., 2015). However, South America remains where BRT systems are mostly embraced as a prime mass transit facility. In the Colombian capital Bogota, the TransMilenio BRT was launched with instant success and decreased average travel time by 32% while increasing land price along the corridor, growing tax revenues, reducing pollution, and creating job opportunities (Turner et al., 2012).

The World Bank and Lebanese officials aim to follow suit by introducing a BRT system that can relieve the bill and burden of traffic congestion. The system will run along the northern coastal highway, with the first phase extending from Tabarja (TB27 in Figure 7) towards Charles Helou station (TB1 is Figure 7) in Beirut. The proposed BRT alignment will mainly serve commuters flowing into Beirut through its northern entrance where congestion is at its worst.

The proposed alignment will run a distance of 24 km with 28 stations spaced at 850-m intervals. Buses will run on two dedicated lanes (one per direction) that will be built in the middle of the existing highway. Bus stations are to be provided in the middle of the two dedicated lanes for smooth boarding/alighting, and pedestrian bridges will connect commuters to the BRT. Buses will operate at pre-defined headways and follow reliable schedules that are shared online and projected on screens at stations (CDR/World Bank, 2017). The proposed BRT layout at stations is shown in Figure 6.

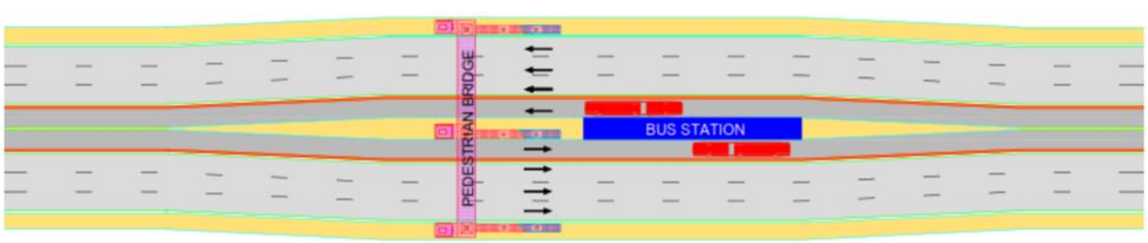

Figure 6: BRT Layout at Stations (CDR/World Bank, 2017)

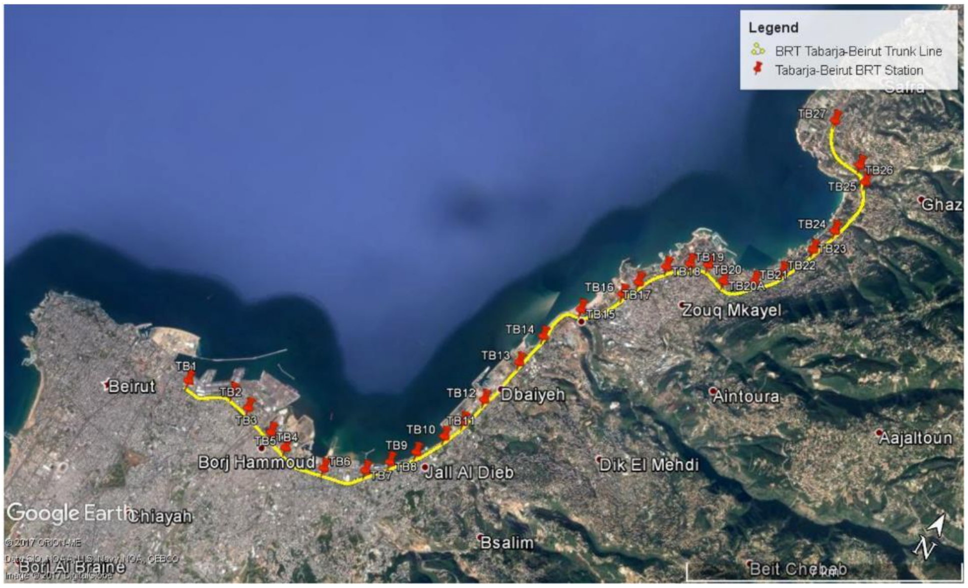

Figure 7: Proposed BRT Alignment (CDR/World Bank, 2017)

4.1.3. Purpose of the Case Study

The case study investigates the potential of ridesourcing in Lebanon in terms of its complementarity to mass transit systems and specifically as a feeder to the proposed Beirut BRT. The study focuses only on trips entering Beirut during the morning peak through its northern entrance in accordance with BRT coverage. The study was limited to current car users as these account for the majority of motorized trips circulating in the GBA. This approach also allows to reduce the number of alternatives in the model as only two main modes will be considered: car and BRT.

4.2. Study Area

The study area is delineated in a way to cover the majority of regions where BRT trips are expected to originate or be destined while keeping data collection feasible. The case study analyzes trips entering into Beirut during the morning peak. As such, the study area is divided into origin zones where BRT trips originate and destination zones where trips are headed. Some zones are strictly origins or destinations, while others can serve as both depending on their relative location in the study area and relative to the BRT alignment.

Since travel times and costs vary significantly for different trip end nodes (trip distance can range from 3 km[1] up to over 40 km), the study area was divided into 9 origin zones (1 to 9 in Figure 8) and 8 destination zones (A to H in Figure 8). Zones 6, 8, and 9 can also serve as destinations for trips originating at zones 1, 2, or 3 due to the large distance traveled by BRT compared to the access/egress distances which makes BRT trips more attractive. Zones are defined based on traditional traffic analysis zones of Lebanon and the relative location to the BRT alignment. For example, a large zone in proximity of the BRT is divided into two sub-zones: one where walking to the BRT is feasible, and the other beyond walking distance (assumed around 750m) to the BRT. Coastal municipalities are agglomerated into zones where walking is feasible as access and/or egress mode, while municipalities away from the BRT alignment are grouped separately. Smaller and more refined zones are defined for areas where population and demand are expected to be high and larger zones are adopted for areas of lower expected demand.

The BRT pre-feasibility report estimates that the largest portion of demand will be from areas adjacent to the BRT alignment (northern regions of GBA, Jounieh, and Tabarja, represented as zones 2, 3, 6, 8, and 9) as commuters residing there can easily board the new proposed transit system and will avoid long stretches of traffic on the highway (World Bank, 2015). Zones beyond walking distance to the BRT alignment can also be served by the system due to motorized feeder lines. The typical interconnectivity ratio, which is a measure of access

[1] Trips shorter than 3 km were not considered as these would have a lower incentive to switch to BRT compared to longer trips.

and egress time as a proportion of total travel time, typically falls between 0.2 and 0.5 (Krygsman et al., 2004) with a mean of around 0.4 (Goel and Tiwari, 2016). The study area was bounded based on an interconnectivity ratio of around 0.5 which verifies that access and egress trips combined are not longer than the BRT trip itself. Therefore, regions within a practical access distance to the BRT were also included as possible trip origins (zones 1, 4, 5, and 7). Municipal Beirut (zones A to C) and northern regions of Greater Beirut where main corporations and universities are located (zones D to H, 6, 8, and 9) are considered valid work/college destinations for the purposes of this study.

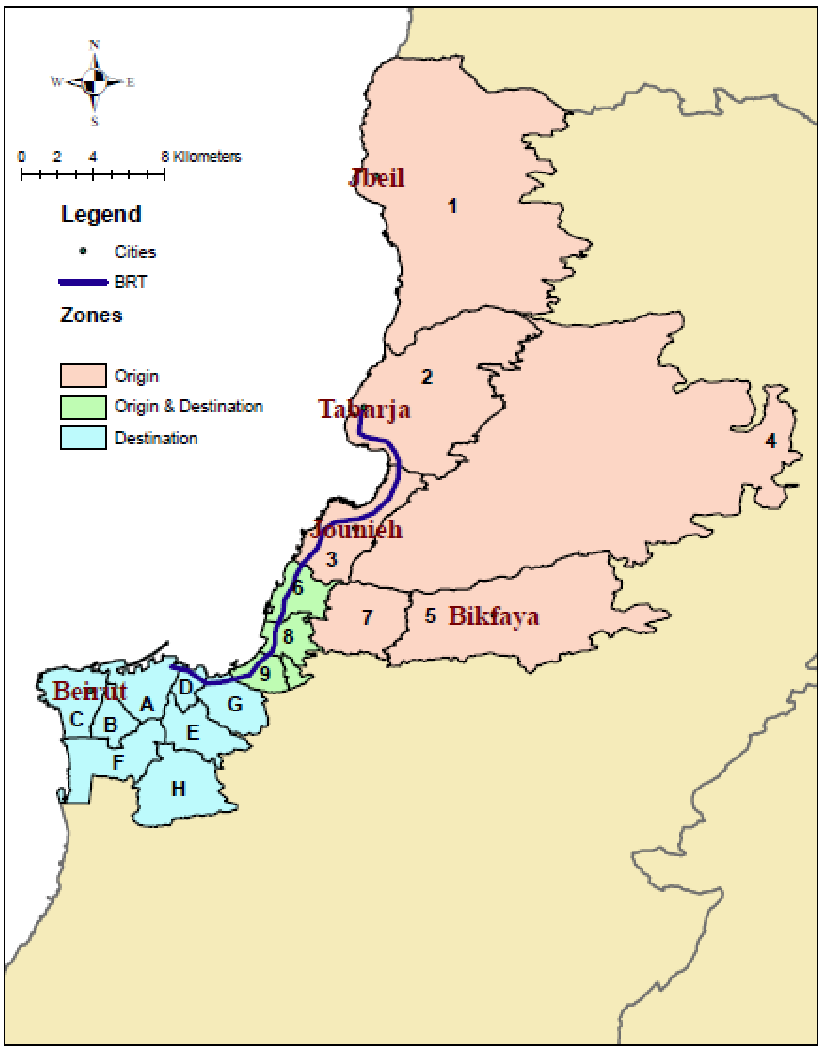

Figure 8: Study Area

4.3. Survey Design

Data was collected by means of a questionnaire tailored for the purpose of this case study. The survey was approved by the Institutional Review Board (IRB) at the American University of Beirut in November 2018, and is provided in Appendix A. The questionnaire consists of 6 sections. The first section contained questions determining eligibility to participate in the survey while the remaining sections were designed to collect two types of data: revealed preference data and stated preference data.

4.3.1. Screening Criteria

An individual is eligible for participation in the study if the following criteria are met:

- ✓ The individual must be an adult (18 years or older).
- ✓ The individual is a full time or part time worker/student.
- ✓ The individual commutes to work/college by private car as driver or as passenger on board.
- ✓ The individual's work/college trip involves commuting on the coastal highway (or any parallel road such as the sea-side road) for 3 km or more.
- ✓ The individual's residence is located within zones 1 to 9 (Figure 8)
- ✓ The individual's work/college destination is within zones A to H (Figure 8)
- ✓ If the individual lives in zones 1, 2, or 3, then zones 6, 8, and 9 are also possible destinations in addition to zones A to H.
- ✓ For individuals residing in zones 4 to 9, only zones A to H are possible destinations.

4.3.2. Revealed Preference Data

The revealed preference part of the survey consists of four separate sections, in addition to the current travel itinerary of the respondent which was already acquired in the screening phase. Section 2 inquires about the characteristics of public transportation with questions about the availability of nearby stations in the vicinity of the respondent's residence, in addition to the frequency of public transportation usage.

Section 3 investigates the attributes of the respondent's typical commute to work/college with questions about time of departure, trip distance and duration, satisfaction with the commute, parking arrangement, and flexibility of work/college schedule.

Section 5 incorporates attitudinal statements about cars, existing buses, the proposed BRT system, and ridesourcing. The respondent is also asked about previous usage of ridesourcing to assess the familiarity with the service and the impact of awareness on the overall adoption of the service. As for attitudinal statements, they allow participants to express their position towards the presented statements based on a 5-point scale where 1 represents a strong disagreement and 5 corresponds to a strong agreement. This type of data is useful for latent variables models in which indicators can capture the respondent's attitudes and perceptions.

Lastly, section 6 collects socio-economic details of the respondent including gender, age, educational level, household size, driver licenses, and income.

4.3.3. Stated Preference Data

Since the BRT is not yet operational in Lebanon, mode choice data is collected through a stated preference survey. Section 4 of the questionnaire presents 3 hypothetical scenarios to each respondent and asks them to select their preferred travel alternative. This section provides an overview of the scenario design including the variables and levels presented in these scenarios.

4.3.3.1. Overview of Scenarios

Stated preference data constitutes the core for modeling and analysis in this study. Scenarios are presented to capture travel mode preferences of participants based on a set of included variables. First, a typical BRT trip was divided into three distinct stages (Figure 9):

1. Access stage: this covers traveling from home to the closest BRT station at which commuters can board BRT buses.
2. Main transport: this corresponds to traveling by BRT from the boarding station to the station where the commuter would alight the BRT.
3. Egress stage: this covers traveling from the alighting station to the final work/college destination.

Respondents were also provided with a broad description of the characteristics of the proposed BRT assuming that some might not be aware of the system. The notion of ridesourcing was also explained ahead of the scenarios to make sure that all respondents understand the features that differentiate it from traditional travel modes.

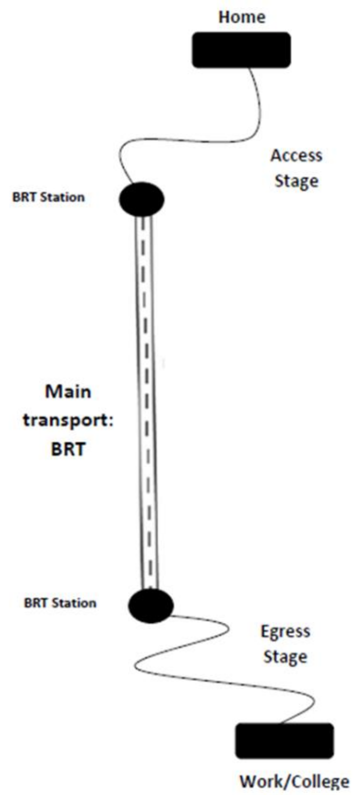

Figure 9: Three Stages of a Typical BRT Trip

Respondents can choose to travel by private car (as they currently do) or by BRT complemented by their preferred access and egress modes. Respondents can choose one of seven provided access modes: park and ride, walking[2], bus, taxi, jitney (mainly known as service in the Lebanese market) which is a shared taxi that can pick-up and/or drop-off passengers at any point along its route, ridesourcing (private), and ridesourcing (shared). Egress modes are the same as access modes but without park and ride as commuters will not have access to their cars at that stage of the trip. Accordingly, 42 combinations of access and egress modes are possible for BRT trips which yields 43 possible options for the respondent to choose from after accounting for

[2] Walking is available as access mode for zones 2, 3, 6, 8, and 9, and as egress mode for zones A, D, G, 6, 8, and 9.

private cars. Including all combinations as separate options into a single experiment will lead to complex choice tasks. Therefore, the selection process is divided into three steps (see Figure 10):

- **Step 1: Preferred BRT Trip:**

In this step, the respondent is assumed to use the BRT over the line-haul segment and is asked to select his/her preferred door-to-door trip. Two independent selections are made: one for the preferred access mode and another for the egress mode, both based on the provided attribute values of travel times and costs. Attribute values are defined based on the actual origin and destination zones of the respondent.

- **Step 2: Choice Confirmation:**

In this step, travel cost and time components are aggregated for the overall BRT trip (including the line-haul segment) based on selections made in step 1, and a table including the total travel time and total cost is provided to the respondent. The respondent can confirm his/her picks and proceed to step 3, or choose to go back to step 1 and select other feeder modes.

- **Step 3: Choice between Preferred BRT Trip and Private Car:**

By now, the respondent has already selected a preferred overall BRT trip. The final step of the scenario is to choose between this BRT trip and using the car all the way (for given hypothetical time and cost values based on the origin and destination zones of the respondent) to check whether the respondent will switch to the BRT or keep commuting by car.

The same totals obtained in step 2 for the overall trip are shown in a table alongside travel times and costs for using the car all the way, and the respondent is asked to make a choice between the car and the BRT based on the presented values.

This procedure allows to capture users' preferences for transit feeder modes while also assessing the potential for switching from private cars to transit. The adopted design also simplifies the choice process without compromising relevant information. Figure 10 illustrates all three steps of a typical scenario.

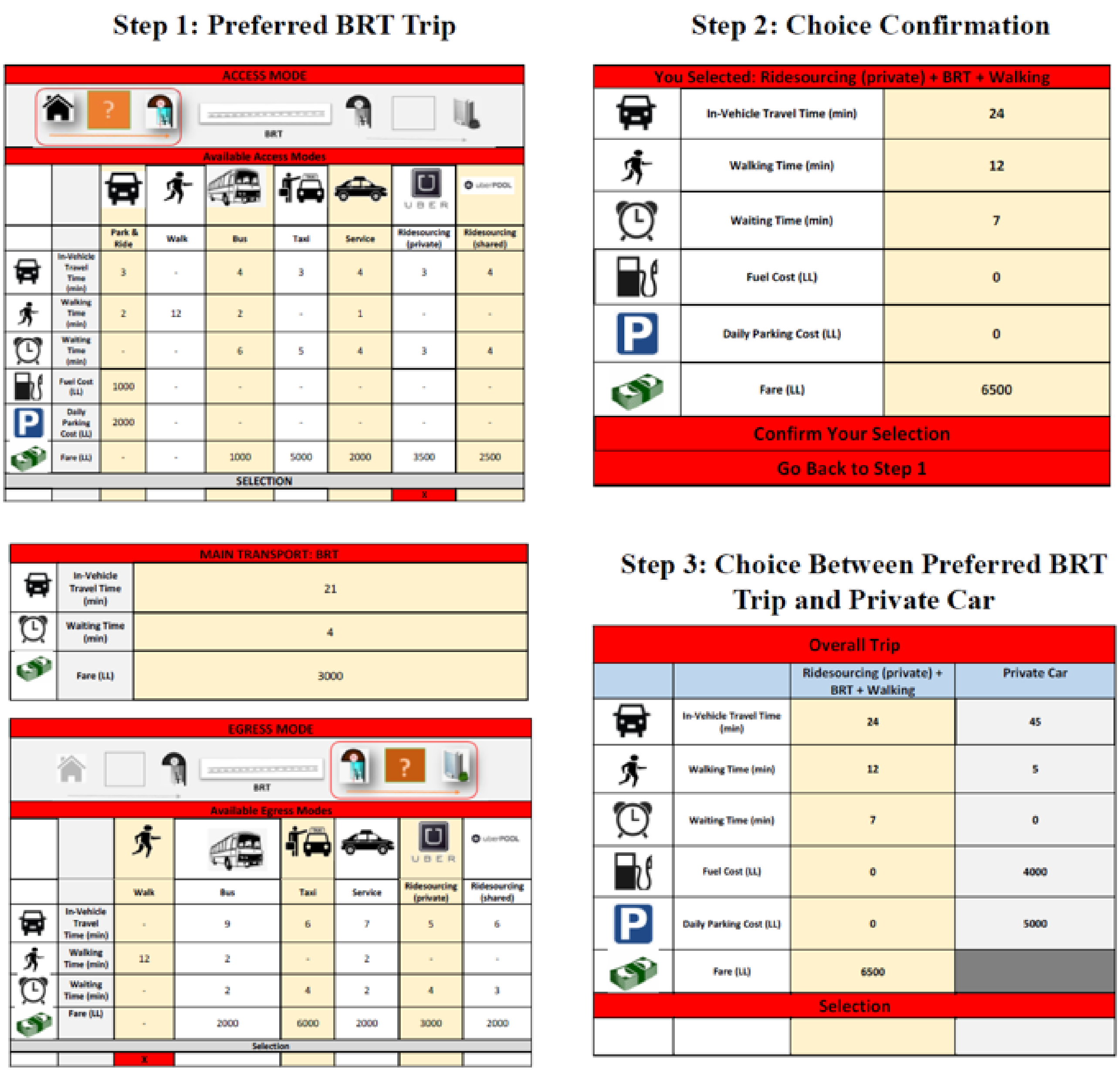

Figure 10: Overview of a Typical Scenario

4.3.3.2. Variables and Levels

As seen in Figure 10, travel time and cost attributes are presented through different sub-categories. Fuel cost, daily parking cost, and trip fares are provided separately. This allows testing users' sensitivity to different cost components, with previous studies revealing that commuters are more sensitive to parking cost and ticket prices than they are to fuel price

(Arentze et al., 2013). In-vehicle travel time, walking time, and waiting time are presented separately for the same purposes.

As stated in section 4.2, the study was divided into multiple zones due to differences in travel time and cost across different zones. Based on the adopted zonal configuration, 81 origin-destination combinations are possible, with each of them having different travel characteristics. A unique set of levels is defined for each origin-destination pair to make sure that respondents are presented with realistic values for the attributes of their trip. Each set includes all attributes that are presented in a typical scenario, with four levels defined for each attribute in the scenario tables. Scenarios are generated based on the random design approach (Walker et al., 2017), with 3 scenarios presented to each respondent.

The chosen levels cover a range as wide as possible while ensuring that all values remain realistic. For example, the four levels for in-vehicle travel time by car are defined in a way to have an optimistic level, assuming that congestion is relieved after the BRT implementation, a pessimistic level, assuming congestion becomes more severe after reducing traffic lanes to accommodate the BRT, and the two remaining levels are slight variations of the current typical travel times, which are obtained from Google Maps for the AM peak period. As an example, the following three tables provide the adopted levels for access, main, and egress modes for trips originating at zone 7 and destined to zone A.

Table 2: Variables and Levels for Access Modes for Trips from Zone 7 to Zone A

Variable	Access Mode[*]	Level 1	Level 2	Level3	Level4
In-Vehicle Travel Time (min)	Park & Ride	6	8	11	12
	Bus	12	14	15	16
	Jitney	10	11	12	13
	Taxi	13	14	15	16
	Ridesourcing (Private)	9	10	12	13
	Ridesourcing (Shared)	11	12	13	14
Waiting Time (min)	Park & Ride	N/A			
	Bus	1	3	5	6
	Jitney	3	4	5	7
	Taxi	5	7	8	10
	Ridesourcing (Private)	2	3	5	6
	Ridesourcing (Shared)	2	3	5	7
Walking Time[**] (min)	Park & Ride	1	2	3	4
	Bus	3	6	8	10
	Jitney	1	2	4	5
	Taxi	N/A			
	Ridesourcing (Private)	N/A			
	Ridesourcing (Shared)	N/A			
Fuel Cost (L.L.[***])	Park & Ride	1,000	1,500	2,000	3,000
	Bus	NA			
	Jitney	NA			
	Taxi	NA			
	Ridesourcing (Private)	NA			
	Ridesourcing (Shared)	NA			
Daily Parking Cost (L.L.[***])	Park & Ride	1,500	2,000	2,500	3,000
	Bus	NA			
	Jitney	NA			
	Taxi	NA			
	Ridesourcing (Private)	NA			
	Ridesourcing (Shared)	NA			
Fare (L.L.[***])	Park & Ride	NA			
	Bus	1,000	1,500	2,000	2,500
	Jitney	2,000	2,500	3,000	4,000
	Taxi	4,000	5,000	7,000	8,000
	Ridesourcing (Private)	3,000	4,000	5,000	7,000
	Ridesourcing (Shared)	1,500	2,500	3,000	4,000

[*] Walking is also available as access mode for zones adjacent to the BRT alignment (zones 2, 3, 6, 8, and 9). Walking time is the only variable of interest when walking is the access mode.
[**] Walking time is only considered for modes that lack the flexibility to pick commuters from their doorsteps and drop them right at stations like bus and jitney. Park and ride includes a short walking time from the parking to the station.
[***] 1 USD = 1,500 L.L. at the time the survey was conducted.

Table 3: Variables and Levels for Main Transport Modes for Trips from Zone 7 to Zone A

Variable	Main Mode	Level 1	Level 2	Level3	Level4
In-Vehicle Travel Time (min)	Car	40	50	55	65
	BRT	13	15	16	19
Waiting Time (min)	Car			NA	
	BRT	1	2	3	4
Walking Time (min)	Car	5	8	10	15
	BRT	1	1	2	2
Fuel Cost (L.L.)	Car	2,500	3,000	3,500	4,000
	BRT			NA	
Daily Parking Cost (L.L.)	Car	6,000	8,000	1,0000	1,2000
	BRT			NA	
Fare (L.L.)	Car			NA	
	BRT	1,500	2,000	3,000	4,000

Table 4: Variables and Levels for Egress Modes for Trips from Zone 7 to Zone A

Variable	Egress Mode*	Level 1	Level 2	Level3	Level4
	Walking			NA	
	Bus	11	13	14	15
In-Vehicle Travel Time (min)	Jitney	10	11	12	13
	Taxi	7	9	10	11
	Ridesourcing (Private)	8	9	10	11
	Ridesourcing (Shared)	8	9	11	12
	Walking			NA	
	Bus	1	2	3	4
Waiting Time (min)	Jitney	1	2	3	4
	Taxi	1	2	3	4
	Ridesourcing (Private)	1	2	3	4
	Ridesourcing (Shared)	1	2	3	4
	Walking	5	7	10	15
	Bus	2	3	4	5
Walking Time** (min)	Jitney	1	2	4	5
	Taxi			NA	
	Ridesourcing (Private)			NA	
	Ridesourcing (Shared)			NA	
	Walking			NA	
	Bus	1,000	1,500	2,000	2,500
	Jitney	1,000	2,000	3,000	4,000
	Taxi	4,000	5,000	6,000	8,000
	Ridesourcing (Private)	2,000	3,000	4,000	5,000
	Ridesourcing (Shared)	1,000	1,500	2,000	3,000

* Walking is only available as egress mode for zones adjacent to the BRT alignment (zones A, D, and G). Walking time is the only variable of interest when walking is the egress mode.

** Walking time is only considered for bus and jitney which lack the flexibility to pick commuters from their doorsteps and drop them right at stations.

4.4. Sampling Plan and Data Collection

This section goes over the determination of sample size and distribution over the different zones alongside the adopted sampling technique and data collection.

4.4.1. Sample Size

The sample needed for estimation of a proportion of the population with a particular characteristic (e.g. the percentage that will switch from car to BRT) is calculated using the following equation:

$$N_S = \frac{Z_{\alpha/2}^2 \times p(1-p)}{d^2} \qquad (17)$$

Where p is the actual proportion of the population, $Z_{\alpha/2}$ is the Z -value extracted from the standard normal distribution table that corresponds to a two tailed significance level α, and d is the allowable error between the sample and the population proportion. An allowable error of 0.05 will be adopted, with p set at 0.5 as this value maximizes the sample size when no better estimate of p can be used. As for α, the most common values in transportation planning practice are 0.05 and 0.10 which imply sample sizes of 384 and 271, respectively.

Accordingly, a sample size of 400 was adopted, which was also consistent with the available budget. However, it must be noted that equation (17) is used to estimate a proportion of the population based on a binary Bernoulli outcome, such as the proportion using the BRT rather than the preferred mode combination of a multi-modal trip. While our experimental design is more complex than a Bernoulli experiment, this remains the best guideline for this purpose and a sample of 400 participants is sufficient in general for standard discrete choice models.

4.4.2. Sampling Plan

The next step was to adopt a sampling strategy to distribute it over the study area. Stratified random sampling was adopted based on the exogenous variable: $\frac{IVTT_{car}}{IVTT_{BRT}+2\times IVTT_{Acc}}$, where $IVTT_{car}$ and $IVTT_{BRT}$ represent in-vehicle travel time by car and BRT, respectively, and $IVTT_{Acc}$ is the in-vehicle travel time to access the BRT by car. The exogenous variable gives an indication of the ratio of travel time by car to travel time by BRT, and stratified sampling was adopted because different behaviors are expected for different values of the exogenous variables. A large ratio reflects that traveling by car is more time consuming than traveling by BRT. Hence, the larger the ratio, the more likely commuters are to use the BRT. Twice the access travel time is used since egress time cannot be controlled when sampling based on residence location (sampling does not consider work/college location).

As seen in Table 5, the 9 origin zones are divided into 4 strata based on the corresponding value of the exogenous variable. Stratum 1 is assigned only 10% of the total sample size as private cars are expected to be more attractive in this case. Stratum 4 is assigned 20% of the total sample size. For this stratum, BRT should be significantly faster than private cars as BRT riders skip long stretches of congestion during their trip that is mostly along the highway. Responses from these zones will reveal whether commuters have strong preference towards private cars and whether travel time is the main factor in mode choice. As for strata 2 and 3, they are attributed 35% each of the total sample since this is where the trade-off in variables is most significant due to relatively close travel times between the BRT and the private car, with a small advantage to the BRT. Hence, these strata can give a clearer insight about how the trade-off between different variables affects overall mode choice. It must be noted that stratification does not affect model estimation but affects forecasting for which proper weights will have to be defined.

Table 5: Stratified Sample

Stratum	Interval for $\frac{IVTT_{car}}{IVTT_{BRT}+2\times IVTT_{Acc}}$	Zones	Share of Sample (%)
1	[0, 1[	5	10
2	[1, 1.5[	1, 2, 4	35
3	[1.5, 2[	3, 7	35
4	[2, ∞[	6, 8, 9	20

Within each stratum, responses are distributed over zones based on population estimates obtained from TMS Consult, a local transportation firm. Each zone is sub-divided into up to 8 sub-zones (A' to H') to ensure that the sample is well distributed over the area, and observations are distributed over sub-zones proportionally to their population. The following table shows how the sample is distributed over zones and sub-zones:

Table 6: Sample Distribution over Zones and Sub-Zones

N=400									
Zone / Sub- Zone	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	51	24	115	66	40	13	25	35	31
A'	5	5	35	3	8	5	5	14	13
B'	8	5	40	7	8	3	5	14	6
C'	10	2	40	13	4	5	5	7	6
D'	8	2	NA	13	8	NA	5	NA	6
E'	5	5	NA	3	4	NA	5	NA	NA
F'	5	5	NA	7	4	NA	NA	NA	NA
G'	5	NA	NA	13	4	NA	NA	NA	NA
H'	5	NA	NA	7	NA	NA	NA	NA	NA

4.4.3. Data Collection

Data collection was performed in January and February 2019 by a professional survey company. The interviewers were trained on the topic to be able to handle any sort of clarification about the included specifications, or inquiry about information beyond the provided details.

400 respondents were interviewed in their homes by trained interviewers and selected as in Table 6, with each respondent receiving 3 different scenarios for a total of 1200 choice experiments. The geographical coordinates of residences were recorded using tablets with GPS to make sure that the sampling plan was respected. The sample is dispersed over the study area as shown in Figure 11.

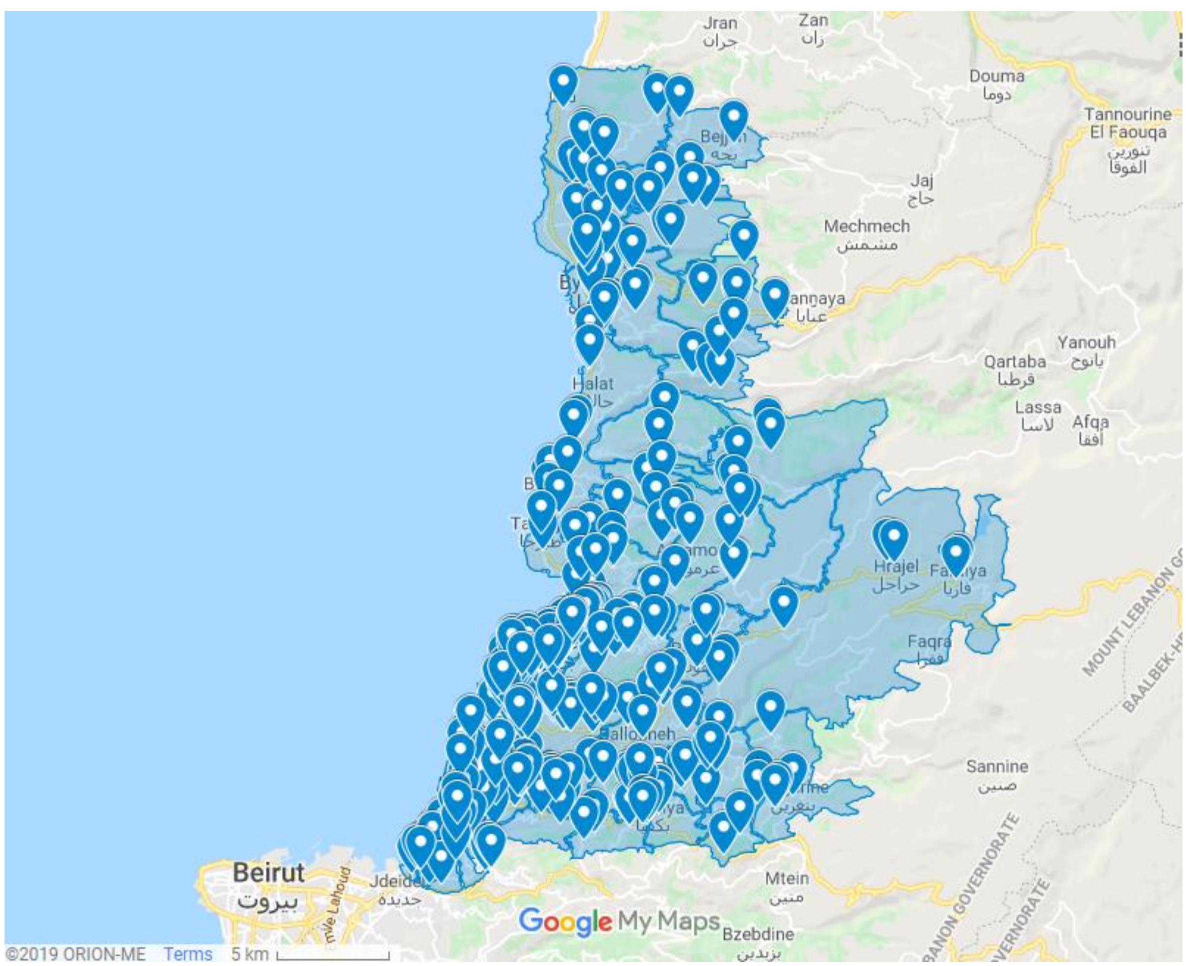

Figure 11: Spatial Distribution of the Sample over the Study Area

4.5. Descriptive Analysis

891 respondents were approached in order to obtain 400 completed questionnaires, for a response rate of around 45%. Out of the 491 rejections, 175 were refusals and 316 were not eligible to participate for one of the following reasons: retired or unemployed respondent (43%), commute mode is not private car (38%), work/study outside of the study area (10%), distance commuted on coastal highway or parallel roads is below 3 km (5%), or zero car ownership (4%).

Responses were also reviewed to identify potential data issues. Choices reveal that taxi was not popular as feeder mode with only 3 and 8 selections for access and egress stages, respectively, out of 1200 scenarios in total. This set was not sufficient to estimate coefficients specific to taxi alternatives. As such, the 8 respondents who chose taxi were eliminated from the data set which left a sample size of 392.

This section summarizes the performed descriptive analysis of the final data set and describes the sample demographics, mode choice, socio-economics, and correlations between different factors and BRT and ridesourcing usage for the 392 responses used in modeling.

4.5.1. Sample Demographics

The sample demographic and socio-economic characteristics obtained from the collected responses are summarized in Table 7. This analysis is performed to assess the representativeness of the sample.

Table 7: Distribution of Sample Demographic and Socio-Economic Characteristics (N = 392)

Survey Question	Option	Percentage of Respondents
Destination Zone	A	33.67
	B	15.82
	C	16.84
	D	9.44
	E	5.36
	F	3.06
	G	5.61
	H	2.30
	6	2.81
	8	2.55
	9	2.55
Main Occupational Status	Full time worker	90.56
	Part time worker	3.57
	Full time student	5.36
	Part time student	0.51
Household Car Ownership	1	30.61
	2	50.26
	3	14.29
	4	2.81
	5+	2.04
Public Transportation Usage Frequency	More than once a week	0.00
	About once a week	6.63
	Few times a month	6.12
	About once a month	2.30
	Several times a year	6.38
	About once or twice a year	8.42
	Never	70.15
Flexibility of Work Arrangement	Flexible arrival and departure	8.16
	Flexible arrival or departure	26.28
	Not flexible	65.56
Used Ridesourcing Previously	Yes	13.01
	No	86.99
Gender	Male	62.76
	Female	37.24

Table 7 (Cont.): Distribution of Sample Demographic and Socio-Economic Characteristics (N = 392)

Survey Question	Option	Percentage of Respondents
Age	18-24	7.91
	25-29	13.27
	30-39	24.74
	40-49	35.71
	50-64	17.60
	64+	0.77
Highest Education Level	Less than high school diploma	4.85
	High school diploma	17.35
	Technical school	14.54
	Some college	17.35
	Bachelor Degree	42.35
	Masters/PhD	3.57
Household Size	1	4.08
	2	9.44
	3	19.13
	4	38.27
	5	21.94
	6+	7.14
Monthly Household Income (L.L.*)	0-1,499,999	0.77
	1,500,000-2,999,999	31.89
	3,000,000-4,499,999	25.51
	4,500,000-5,999,999	16.33
	6,000,000-7,499,999	4.85
	7,500,000-9,999,999	5.10
	10,000,000-14,999,999	1.02
	I don't know / No answer	14.54

*1 USD = 1,500 L.L.

As shown in the table above, around 66% of respondents' commutes are destined to Municipal Beirut (Zones A, B, and C) where the largest firms and universities are located. However, this market segment is over-represented as employment figures from TMS Consult reveal that Municipal Beirut accounts for 55% of employment in the destinations defined in the adopted study area. These figures however do not include students and are national figures in Lebanon that are not based on the proposed layout of the study area.

Full time workers constitute the dominant majority of the sample and frequent public transportation users (on a monthly basis) represent a low share of around 15% which was expected as only car users were included in the study. Car ownership is relatively high with 70% of households owning 2 or more cars. This is much higher than the 25% found by TEAM (1995) in the Greater Beirut Transportation Plan. This can be attributed to the elimination of households with no cars from our study, the growth in car ownership during the last 24 years, and the possibility that car ownership rates are higher outside Greater Beirut as public transportation outside the capital is even more deficient.

Around 63% of the sample are male, and around 95% have a high school diploma with 46% having earned a college degree. The age is well distributed over the sample with the largest portion, around 36%, falling between 40 and 49 years. The average household size of the sample is 3.87 which is comparable to the average of 4.23 obtained from the Central Administration of Statistics' (CAS) Living Conditions Survey in 2007. As for the average household monthly income, over 68% of reported incomes fell below 4,500,000 L.L. (around 3,000 USD) while only 7% exceeded 7,500,000 L.L. (around 5,000 USD).

4.5.2. Mode Choice

The 392 respondents were presented each with 3 different scenarios for a total of 1176 choice experiments. The choices are summarized in Table 8.

Table 8: Mode Choice Results

Main Mode	Percentage of Scenarios (1176 Scenarios)
Car	65.48
BRT	34.52
Access Mode	**Percentage of Scenarios where BRT was Chosen (406 Scenarios)**
Park & Ride	45.91
Walk	30.05
Bus	8.17
Jitney	2.16
Ridesourcing (Private)	2.64
Ridesourcing (Shared)	11.06
Egress Mode	**Percentage of Scenarios where BRT was Chosen (406 Scenarios)**
Walk	33.89
Bus	9.62
Jitney	18.03
Ridesourcing (Private)	3.13
Ridesourcing (Shared)	35.34

In 34.52% of scenarios, the choice was BRT as mode of main transport while the choice in the remaining scenarios was not to switch from private cars. Among the scenarios where BRT was chosen, park and ride was the most popular access mode with a share of around 46% while walking accounted for 30% of access trips and 34% of egress modes despite not being feasible at all zones. For zones where walking is available, 43% of BRT users chose it for access while 52% selected is for egress. Shared ridesourcing was much more popular than private ridesourcing revealing that public transit users value cost more than privacy in feeder trips. It must be noted

that 59% of respondents selected car for the three scenarios revealing that some commuters have strong preference for driving, while 28% selected BRT for main travel in all scenarios reflecting a market segment that is highly enthusiastic to have and use mass transit for work/study trips.

4.5.3. Socio-Economic Characteristics and Correlation to Mode Choice

In this section, the effect of demographic and socio-economic characteristics on BRT and ridesourcing usage is assessed. This helps in identifying key variables that can be included in the model. Table 9 describes the main findings.

Table 9: Demographic and Socio-Economic Variables in Relation to BRT and Ridesourcing Usage

Survey Question	Option	Percentage of Scenarios Choosing BRT	Percentage of BRT Users Choosing Ridesourcing**
Household Car Ownership	1	35.83	36.43
	2	34.52	43.14
	3	29.17	55.10
	4	33.33	45.45
	5+	54.17	38.46
Public Transportation Usage Frequency	About once a week	41.03	18.75
	Few times a month	66.67	39.58
	About once a month	96.30	53.85
	Several times a year	34.67	38.46
	About once or twice a year	50.51	66.00
	Never		
Flexibility of Work Arrangement	Flexible arrival and departure	38.54	24.32
	Flexible arrival or departure	26.54	29.27
	Not flexible	37.22	48.43
Used Ridesourcing Previously	Yes	45.75	62.86
	No	32.84	38.10
Gender	Male	26.42	37.44
	Female	48.17	46.92

Table 9 (Cont.): Demographic and Socio-Economic Variables in Relation to BRT and Ridesourcing Usage

Survey Question	Option	Percentage of Scenarios Choosing BRT	Percentage of BRT Users Choosing Ridesourcing**
Age	18-24	61.29	47.37
	25-29	48.72	46.05
	30-39	45.02	52.67
	40-49	23.33	30.61
	50-64	19.81	21.95
	64+	33.33	66.67
Highest Education Level	Less than high school diploma	70.18	25.00
	High school diploma	37.75	36.36
	Technical school	32.16	40.00
	Some college	35.29	30.56
	Bachelor Degree	30.12	54.00
	Masters/PhD	28.57	75.00
Household Size	1	37.50	61.11
	2	37.84	50.00
	3	35.56	47.50
	4	32.89	35.14
	5	36.82	37.89
	6+	23.19	68.75
Monthly Household Income (L.L.*)	0-1,499,999	55.56	40.00
	1,500,000-2,999,999	19.47	27.40
	3,000,000-4,499,999	33.33	31.00
	4,500,000-5,999,999	48.44	47.31
	6,000,000-7,499,999	59.65	38.24
	7,500,000-9,999,999	63.33	55.26
	10,000,000-14,999,999	25.00	0.00
	I don't know / No answer	35.09	23.98

* 1 USD = 1,500 L.L.

** Using private and/or shared ridesourcing for access and/or egress stages

The analysis reveals no clear effect of car ownership on BRT ridership. Frequent public transportation users are more likely to switch to the BRT than those who rarely use transit. Females and commuters who are familiar with ridesourcing are also more in favor of the new transit system. BRT ridership is negatively correlated to age with older users embracing the transit system at lower rates than their younger counterparts. Household size and educational level do not seem to have a significant impact on main mode choice, while the relation with respect to monthly family income is ambiguous.

As for ridesourcing, the main socio-economic factors affecting demand are apparently familiarity with the service, flexibility of work arrangement, frequency of public transportation usage, gender, age, and education. The share of ridesourcing increases for commuters with no work flexibility and for those who rarely use public transportation. The share of ridesourcing is inversely proportional to the age of commuters with younger people more likely to use the new mobility concept. Education also reveals a clear relation to ridesourcing usage with more educated segments embracing the service at higher rates. As for gender, ridesourcing is more popular with females than males based on the collected sample.

BRT preference was also assessed based on residence area and destination zone. Residents in zones far from the BRT alignment (zones 5, 1, 4, and 7, ranked by decreasing distance to the BRT) were more reliant on cars, as shown in Figure 12, suggesting that long access trips decrease the attractiveness of the BRT. Long egress trips are also detrimental to the BRT as destination zones that are far from stations had lower BRT shares (zones H, F, G, C, and H as shown in Figure 13, ranked from farthest to closest to the BRT alignment). This suggests that mass transit systems mainly cater for trips starting and ending at the proximity of the alignment with utility gradually decreasing as we move further away from the corridor.

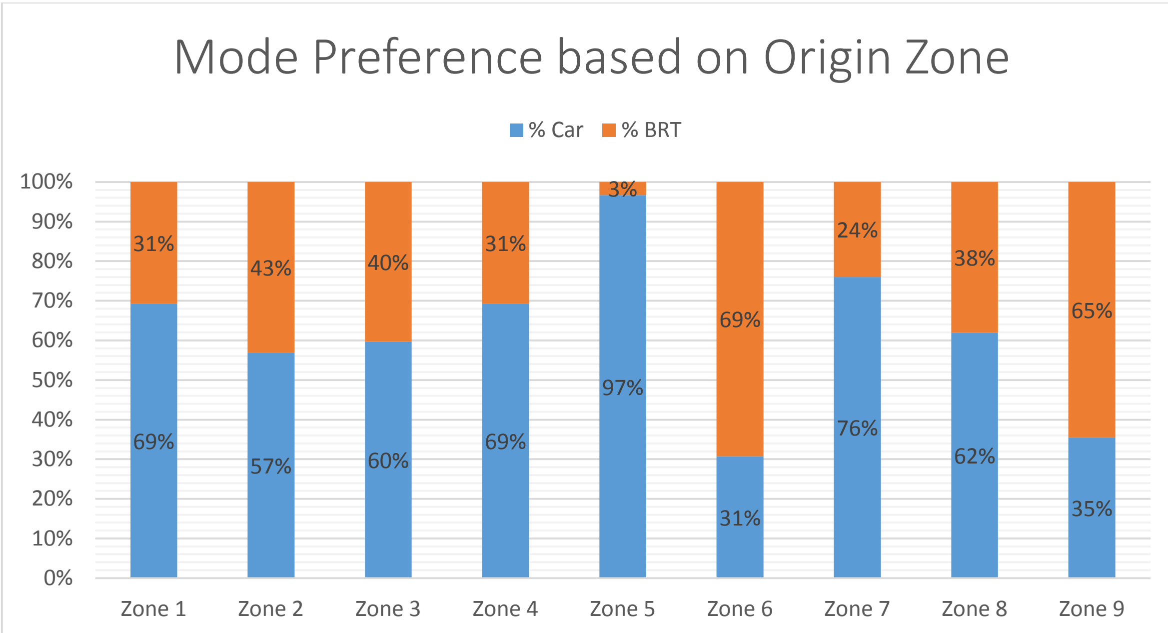

Figure 12: Modal Split between Car and BRT based on Residence Area

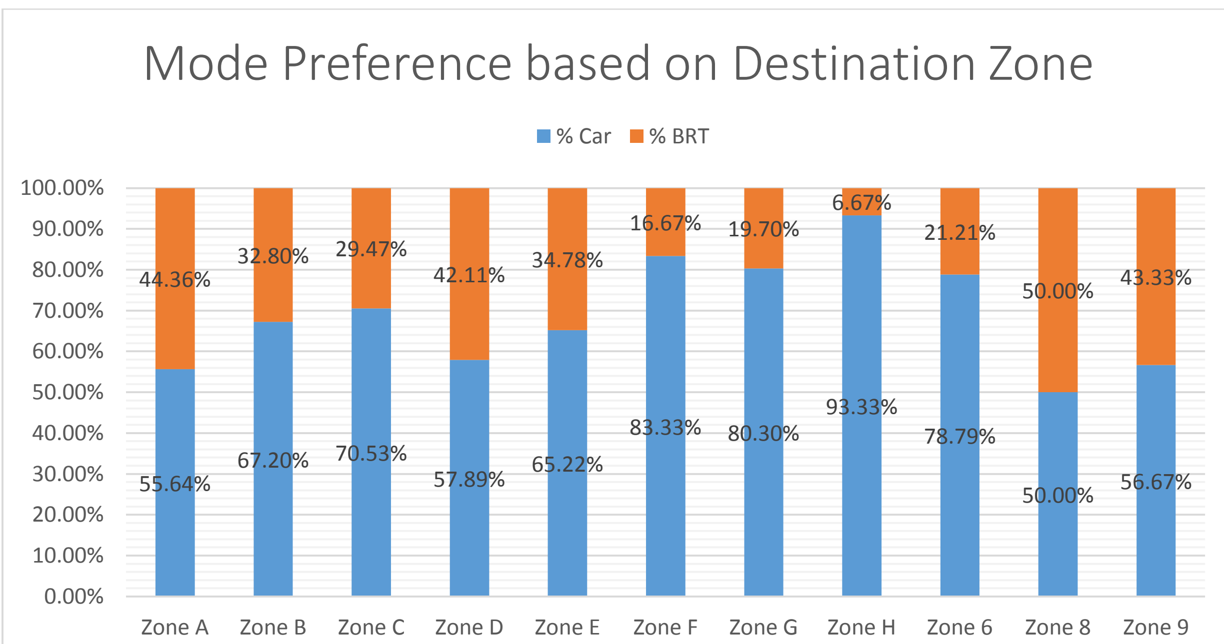

Figure 13: Modal Split between Car and BRT based on Destination Zone

4.6. Demand Modeling

The discrete choice modeling framework developed in Chapter 3 is applied using the data collected to model demand for ridesourcing and other modes as feeders to the planned Beirut BRT. This section covers the assumptions of the case study, the model specification, and the model development.

4.6.1. Assumptions

Several assumptions are made to reduce the complexity of the model and ease its estimation. The main assumptions are the following:

- The alternative specific constant for a particular mode is equal for all travel stages. That is, $\alpha_u^{Acc} = \alpha_u^{Egr} = \alpha_u \qquad \forall u \in U = A \cap E$
- Similarly, the error components are assumed to be specific to the mode of travel rather than the trip stage. One error component is defined by mode assuming that attitudes towards a particular feeder are independent of trip stage. This assumption was used to reduce the random terms in the model which reduces the computational burden involved in model estimation.

  $\omega_u^{Acc} = \omega_u^{Egr} = \omega_u \qquad \forall u \in U = A \cap E$

  Therefore, the number of error components for feeders equals the size of the set $F = \{A \cup E\}$ which includes all feeder modes but avoids duplication.
- Private car is the only uni-modal trip considered, with traditional public transportation modes like buses, taxis, and jitneys not included for all-the-way trips. That is mainly to reduce the number of alternatives in model estimation but also because public

transportation, as discussed previously, has a low share of overall trips with the car dominance prevailing. Accordingly, the success of the BRT highly depends on convincing drivers to switch. Thus, the model estimated in this thesis is a switching model from car to BRT.

- The BRT is the other main transport mode considered as it will be, once implemented, the only high capacity transit system operating on the northern entrance to Beirut. Each BRT trip is assumed to require exactly one access trip and one egress trip. No trip can skip one of the stages or use multiple modes for access or egress. This assumption allowed to reduce the complexity of the stated preference design to avoid confusion of participants and ensure responsive and educated selections.
- The alternative specific constant of the car alternative is normalized to zero, while the same is done for the error component of the BRT. The constant of the BRT was also normalized at zero as it is assumed to be incorporated in that of the feeders, with each BRT alternative including two feeders each of which has a specific constant to be estimated.

4.6.2. Model Specification

The systematic utilities are defined by mode of main transport, access mode, and egress mode. The utility of any alternative *j* can then be obtained by combining utilities of modes at different stages. After eliminating taxi from feeder options, we are left with 2 main travel modes, 6 access modes, and 5 egress modes which allows for 31 different travel alternatives. The sets of available modes are defined as follows:

$M = \{Car, BRT\}$

$A = \{Park\ and\ Ride, Walk, Bus, Jitney, Ridesourcing\ (Private), Ridesourcing\ (Shared)\}$

$E = \{Walk, Bus, Jitney, Ridesourcing\ (Private), Ridesourcing\ (Shared)\}$

Three different approaches are tested before selecting a final specification: the first approach considers total travel time with separate coefficients based on trip stage, the second approach is similar to the first one but distinguishes between in-vehicle and out-of-vehicle travel times, while the third approach is similar to the second but adopts different coefficients for in-vehicle travel time of different feeder modes. The three approaches are discussed next, and the most suitable model is selected after estimation in chapter 5 based on the criteria defined in chapter 3. It must be noted that several other approaches were tested but did not lead to significant results.

4.6.2.1. Approach I: Model with Total Travel Time

This approach does not separate between in-vehicle and out-of-vehicle travel time. Instead, it separates travel time based on the stage of the trip (main, access, egress). V', which is the sum of the systematic utility and error components, is defined below for each main, access, and egress mode.

$$V'^{Main}_{Car,n,t} = 0 + \beta_{TT/\ln(dist)\_Car}\frac{TT^{Main}_{Car,n,t}}{\ln(dist)_n} + \beta_{Cost,n}Cost^{Main}_{Car,n,t} + \beta_{Age\_Car}Age_n + \beta_{Flex\_Car}Flexible_n + \beta_{PTuser\_Car}PT\_User_n + \omega_{Car,n} \quad (18)$$

$$V'^{Main}_{BRT,n,t} = 0 + \beta_{TT\_BRT}TT^{Main}_{BRT,n,t} + \beta_{Cost,n}Cost^{Main}_{BRT,n,t} \quad (19)$$

$$V'^{Acc}_{Park\&Ride,n,t} = \alpha_{Park\&Ride} + \beta_{TT\_Feeders} TT^{Acc}_{Park\&Ride,n,t} + \beta_{Cost,n} Cost^{Acc}_{Park\&Ride,n,t} + \omega_{Park\&Ride,n} \tag{20}$$

$$V'^{Acc}_{Walk,n,t} = \alpha_{Walk} + \beta_{TT\_Feeders} TT^{Acc}_{Walk,n,t} + \omega_{Walk,n} \tag{21}$$

$$V'^{Acc}_{Bus,n,t} = \alpha_{Bus} + \beta_{TT\_Feeders} TT^{Acc}_{Bus,n,t} + \beta_{Cost,n} Cost^{Acc}_{Bus,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Bus,n} \tag{22}$$

$$V'^{Acc}_{Jitney,n,t} = \alpha_{Jitney} + \beta_{TT\_Feeders} TT^{Acc}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Acc}_{Jitney,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Jitney,n} \tag{23}$$

$$V'^{Acc}_{Ride(Pri),n,t} = \alpha_{Ride(Pri)} + \beta_{TT\_Feeders} TT^{Acc}_{Ride(Pri),n,t} + \beta_{Cost,n} Cost^{Acc}_{Ride(Pri),n,t} + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \beta_{Flex\_Ride} Flexible_n + \omega_{Ride(Pri),n} \tag{24}$$

$$V'^{Acc}_{Ride(Sha),n,t} = \alpha_{Ride(Sha)} + \beta_{TT\_Feeders} TT^{Acc}_{Ride(Sha),n,t} + \beta_{Cost,n} Cost^{Acc}_{Ride(Sha),n,t} + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \beta_{Flex\_Ride} Flexible_n + \omega_{Ride(Sha),n} \tag{25}$$

$$V'^{Egr}_{Walk,n,t} = \alpha_{Walk} + \beta_{TT\_Feeders} TT^{Egr}_{Walk,n,t} + \omega_{Walk,n} \tag{26}$$

$$V'^{Egr}_{Bus,n,t} = \alpha_{Bus} + \beta_{TT\_Feeders} TT^{Egr}_{Bus,n,t} + \beta_{Cost,n} Cost^{Egr}_{Bus,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Bus,n} \tag{27}$$

$$V'^{Egr}_{Jitney,n,t} = \alpha_{Jitney} + \beta_{TT\_Feeders} TT^{Egr}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Egr}_{Jitney,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Jitney,n} \tag{28}$$

$$
\begin{aligned}
V'^{Egr}_{Ride(Pri),n,t} = {} & \alpha_{Ride(Pri)} + \beta_{TT\_Feeders} TT^{Egr}_{Ride(Pri),n,t} \\
& + \beta_{Cost,n} Cost^{Egr}_{Ride(Pri),n,t} \\
& + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n \\
& + \beta_{Flex\_Ride} Flexible_n + \omega_{Ride(Pri),n}
\end{aligned} \tag{29}
$$

$$
\begin{aligned}
V'^{Egr}_{Ride(Sha),n,t} = {} & \alpha_{Ride(Sha)} + \beta_{TT\_Feeders} TT^{Egr}_{Ride(Sha),n,t} \\
& + \beta_{Cost,n} Cost^{Egr}_{Ride(Sha),n,t} \\
& + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n \\
& + \beta_{Flex\_Ride} Flexible_n + \omega_{Ride(Sha),n}
\end{aligned} \tag{30}
$$

The utility of an alternative is then defined by adding those of its different stages. For example the utility of the Bus-BRT-Jitney alternative is defined as follows:

$$
\begin{aligned}
U_{\substack{Bus-BRT- \\ Jitney,n,t}} = {} & \alpha_{Bus} + \alpha_{Jitney} + \beta_{TT\_Feeders} TT^{Acc}_{Bus,n,t} + \beta_{TT\_BRT} TT^{Main}_{BRT,n,t} \\
& + \beta_{TT\_Feeders} TT^{Egr}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Egr}_{Jitney,n,t} \\
& + \beta_{Cost,n} Cost^{Main}_{BRT,n,t} + \beta_{Cost,n} Cost^{Acc}_{Bus,n,t} \\
& + 2\beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Bus,n} + \omega_{Jitney,n} \\
& + \varepsilon_{Bus-BRT-Jitney,n,t}
\end{aligned} \tag{31}
$$

The car total travel time is interacted with the logarithm of the distance to imply that the marginal disutility of an additional minute is different for short trips and long trips. The logarithm was used since adopting a linear interaction of travel time with distance yields the inverse of the average speed along the trip which is counterintuitive as short and long trips can have similar speed but should not have equal disutility. The base e was used for the logarithm as base 10 results in values below one for trips below 10 km which is not desirable. That problem will not occur with the base e as a minimum highway commute of 3 km is one of the screening criteria. This interaction is adopted only for car travel time as congestion and road design imply that trips of the same distance can require significantly different travel times. This is not the case for BRT which operates on a dedicated lane with more homogeneous travel speeds.

The cost coefficient is defined as a log-normal coefficient to capture unobserved taste variation in cost across individuals (equation 32). Time coefficients are deterministic as their large number requires high computational power when the random specification is adopted. The log-normal specification allows to maintain a negative cost coefficient for all observations which is why it was preferred over the normal distribution (Train, 2009). Error components ω are also defined as the product of a standard deviation σ to be estimated and a random simulated term following the standard normal distribution as shown in equation (33):

$$\beta_{Cost,n} = -e^{\left(\mu_{\beta_{Cost,n}} + \sigma_{\beta_{Cost,n}} \times \Omega_{Cost,n}\right)} \qquad \Omega_{Cost,n} \sim N(0,1) \tag{32}$$

$$\omega_{q,n} = \sigma_{\omega_q} \times \Omega_{q,n} \qquad q \in Q = M \cup A \cup E, \;\; \Omega_{q,n} \sim N(0,1) \tag{33}$$

$\mu_{\beta_{Cost,n}}$ and $\sigma_{\beta_{Cost,n}}$ are, respectively, the mean and standard deviation of the underlying normal parameter across the entire population, with both parameters to be estimated. β_{Cost} can be obtained for each individual through simulation. Table 10 describes all explanatory variables included in the utility functions.

Table 10: Explanatory Variables Used in the Model based on Approach I

Variable	Type	Description
$\boldsymbol{TT^{Z}_{H,n,t}}$	Continuous variable	Total one-way travel time by mode H at stage Z for respondent *n* in scenario *t* (in hours)
$\boldsymbol{Cost^{Z}_{H,n,t}}$	Continuous variable	Cost of one-way trip by mode H at stage Z for respondent *n* in scenario *t* (in 1,000 L.L.)
$\boldsymbol{dist_n}$	Continuous variable	Total one-way trip distance for respondent *n* (in km)
$\boldsymbol{Age_n}$	Continuous variable	Age of respondent *n* (in years), with midpoint value used for the reported range (e.g., 21 is used for the 18-24 range)
$\boldsymbol{Flexible_n}$	Dummy variable	A value of 1 indicates that respondent *n* has a fully or partially flexible work/study arrangement. A value of 0 indicates a non-flexible schedule.
$\boldsymbol{PT\_User_n}$	Dummy variable	A value of 1 indicates that respondent *n* uses public transportation frequently (at least once a month). A value of 0 indicates otherwise.

4.6.2.2. Approach II: Model with Separated In-Vehicle and Out-of-Vehicle Travel Times

This approach is similar to the previous one with the exception that the total travel time is divided into in-vehicle (IVTT) and out-of-vehicle (OVTT) travel time. At the same time, the out-of-vehicle travel time is separated into walking and waiting time to estimate separate coefficients for each variable. The systematic utilities become as follows:

$$V'^{Main}_{Car,n,t} = 0 + \beta_{IVTT/\ln(dist)\_Car} \frac{IVTT^{Main}_{Car,n,t}}{\ln(dist)_n} + \beta_{Walking\_Time} Walking\_Time^{Main}_{Car,n,t} + \beta_{Cost,n} Cost^{Main}_{Car,n,t} + \beta_{Age\_Car} Age_n + \beta_{Flex\_Car} Flexible_n + \beta_{PTuser\_Car} PT\_User_n + \omega_{Car,n} \quad (34)$$

$$V'^{Main}_{BRT,n,t} = 0 + \beta_{IVTT\_BRT} IVTT^{Main}_{BRT,n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Main}_{BRT,n,t} + \beta_{Cost,n} Cost^{Main}_{BRT,n,t} \quad (35)$$

$$V'^{Acc}_{Park\&Ride,n,t} = \alpha_{Park\&Ride} + \beta_{IVTT/\ln(dist)\_Car} \frac{IVTT^{Acc}_{Park\&Ride,n,t}}{\ln(accdist)_n} + \beta_{Walking\_Time} Walking\_Time^{Acc}_{Park\&Ride,n,t} + \beta_{Cost,n} Cost^{Acc}_{Park\&Ride,n,t} + \omega_{Park\&Ride,n} \quad (36)$$

$$V'^{Acc}_{Walk,n,t} = \alpha_{Walk} + \beta_{Walking\_Time} Walking\_Time^{Acc}_{Walk,n,t} + \omega_{Walk,n} \quad (37)$$

$$V'^{Acc}_{Bus,n,t} = \alpha_{Bus} + \beta_{IVTT\_Feeders} IVTT^{Acc}_{Bus,n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Acc}_{Bus,n,t} + \beta_{Walking\_Time} Walking\_Time^{Acc}_{Bus,n,t} + \beta_{Cost,n} Cost^{Acc}_{Bus,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Bus,n} \quad (38)$$

$$V'^{Acc}_{Jitney,n,t} = \alpha_{Jitney} + \beta_{IVTT\_Feeders} IVTT^{Acc}_{Jitney,n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Acc}_{Jitney,n,t} + \beta_{Walking\_Time} Walking\_Time^{Acc}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Acc}_{Jitney,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Jitney,n} \quad (39)$$

$$
\begin{aligned}
V'^{Acc}_{Ride(Pri),n,t} = {} & \alpha_{Ride(Pri)} + \beta_{IVTT\_Feeders} IVTT^{Acc}_{Ride(Pri),n,t} \\
& + \beta_{Waiting\_Time} Waiting\_Time^{Acc}_{Ride(Pri),n,t} \\
& + \beta_{Cost,n} Cost^{Acc}_{Ride(Pri),n,t} + \beta_{Flex\_Ride} Flexible_n \\
& + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Pri),n}
\end{aligned}
\tag{40}
$$

$$
\begin{aligned}
V'^{Acc}_{Ride(Sha),n,t} = {} & \alpha_{Ride(Sha)} + \beta_{IVTT\_Feeders} IVTT^{Acc}_{Ride(Sha),n,t} \\
& + \beta_{Waiting\_Time} Waiting\_Time^{Acc}_{Ride(Sha),n,t} \\
& + \beta_{Cost,n} Cost^{Acc}_{Ride(Sha),n,t} + \beta_{Flex\_Ride} Flexible_n \\
& + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Sha),n}
\end{aligned}
\tag{41}
$$

$$
V'^{Egr}_{Walk,n,t} = \alpha_{Walk} + \beta_{Walking\_Time} Walking\_Time^{Egr}_{Walk,n,t} + \omega_{Walk,n}
\tag{42}
$$

$$
\begin{aligned}
V'^{Egr}_{Bus,n,t} = {} & \alpha_{Bus} + \beta_{IVTT\_Feeders} IVTT^{Egr}_{Bus,n,t} \\
& + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Bus,n,t} \\
& + \beta_{Walking\_Time} Walking\_Time^{Egr}_{Bus,n,t} + \beta_{Cost,n} Cost^{Egr}_{Bus,n,t} \\
& + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Bus,n}
\end{aligned}
\tag{43}
$$

$$
\begin{aligned}
V'^{Egr}_{Jitney,n,t} = {} & \alpha_{Jitney} + \beta_{IVTT\_Feeders} IVTT^{Egr}_{Jitney,n,t} \\
& + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Jitney,n,t} \\
& + \beta_{Walking\_Time} Walking\_Time^{Egr}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Egr}_{Jitney,n,t} \\
& + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Jitney,n}
\end{aligned}
\tag{44}
$$

$$V'^{Egr}_{Ride(Pri),n,t} = \alpha_{Ride(Pri)} + \beta_{IVTT\_Feeders} IVTT^{Egr}_{Ride(Pri),n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Ride(Pri),n,t} + \beta_{Cost,n} Cost^{Egr}_{Ride(Pri),n,t} + \beta_{Flex\_Ride} Flexible_n + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Pri),n} \quad (45)$$

$$V'^{Egr}_{Ride(Sha),n,t} = \alpha_{Ride(Sha)} + \beta_{IVTT\_Feeders} IVTT^{Egr}_{Ride(Sha),n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Ride(Sha),n,t} + \beta_{Cost,n} Cost^{Egr}_{Ride(Sha),n,t} + \beta_{Flex\_Ride} Flexible_n + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Sha),n} \quad (46)$$

For IVTT, it was found that using the car coefficient for park and ride resulted in a better model overall. The rest of the specifications are similar to the first approach, with the exception of some new variables which are defined in Table 11:

Table 11: Explanatory Variables Used in the Model based on Approach II

Variable	Type	Description
$\boldsymbol{IVTT^{Z}_{H,n,t}}$	Continuous variable	Total one-way in-vehicle travel time by mode H at stage Z for respondent *n* in scenario *t* (in hours)
$\boldsymbol{Walking\_Time^{Z}_{H,n,t}}$	Continuous variable	Total one-way walking time by mode H at stage Z for respondent *n* in scenario *t* (in hours)
$\boldsymbol{Waiting\_Time^{Z}_{H,n,t}}$	Continuous variable	Total one-way waiting time by mode H at stage Z for respondent *n* in scenario *t* (in hours)
$\boldsymbol{Cost^{Z}_{H,n,t}}$	Continuous variable	Cost of one-way trip by mode H at stage Z for respondent *n* in scenario *t* (in 1,000 L.L.)

Table 11 (Cont.): Explanatory Variables Used in the Model based on Approach II

Variable	Type	Description
$\boldsymbol{dist_n}$	Continuous variable	One-way door-to-door trip distance for respondent *n* (in km)
$\boldsymbol{accdist_n}$	Continuous variable	One-way access distance for respondent *n* (in km)
$\boldsymbol{Age_n}$	Continuous variable	Age of respondent *n* (in years) , with midpoint value used for the reported range (e.g., 21 is used for the 18-24 range)
$\boldsymbol{Flexible_n}$	Dummy variable	A value of 1 indicates that respondent *n* has a fully or partially flexible work/study arrangement. A value of 0 indicates a non-flexible schedule.
$\boldsymbol{PT\_User_n}$	Dummy variable	A value of 1 indicates that respondent *n* uses public transportation frequently (at least once a month). A value of 0 indicates otherwise.
$\boldsymbol{Ride\_User_n}$	Dummy variable	A value of 1 indicates that respondent *n* used any form of ridesourcing previously in Lebanon or abroad. A value of 0 indicates otherwise.

4.6.2.3. Approach III: Model with IVTT Coefficient Specific to Each Mode

The third approach has the same specification as the second approach with only one exception: instead of using a unified coefficient for the IVTT of all feeders, coefficients are defined by feeder mode. Traditional public transportation modes are assumed to share the same IVTT coefficient while the two ridesourcing options share their own coefficient. The car coefficient for IVTT is still used for park and ride. The coefficients do not change across different trip stages and vary only by mode. The systematic utilities are defined as follows:

$$V'^{Main}_{Car,n,t} = 0 + \beta_{IVTT/\ln(dist)\_Car} \frac{IVTT^{Main}_{Car,n,t}}{\ln(dist)_n} + \beta_{Walking\_Time} Walking\_Time^{Main}_{Car,n,t} + \beta_{Cost,n} Cost^{Main}_{Car,n,t} + \beta_{Age\_Car} Age_n + \beta_{Flex\_Car} Flexible_n + \beta_{PTuser\_Car} PT\_User_n + \omega_{Car,n} \tag{47}$$

$$V'^{Main}_{BRT,n,t} = 0 + \beta_{IVTT\_BRT} IVTT^{Main}_{BRT,n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Main}_{BRT,n,t} + \beta_{Cost,n} Cost^{Main}_{BRT,n,t} \tag{48}$$

$$V'^{Acc}_{Park\&Ride,n,t} = \alpha_{Park\&Ride} + \beta_{IVTT/\ln(dist)\_Car} \frac{IVTT^{Acc}_{Park\&Ride,n,t}}{\ln(accdist)_n} + \beta_{Walking\_Time} Walking\_Time^{Acc}_{Park\&Ride,n,t} + \beta_{Cost,n} Cost^{Acc}_{Park\&Ride,n,t} + \omega_{Park\&Ride,n} \tag{49}$$

$$V'^{Acc}_{Walk,n,t} = \alpha_{Walk} + \beta_{Walking\_Time} Walking\_Time^{Acc}_{Walk,n,t} + \omega_{Walk,n} \tag{50}$$

$$V'^{Acc}_{Bus,n,t} = \alpha_{Bus} + \beta_{IVTT\_BusSer} IVTT^{Acc}_{Bus,n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Acc}_{Bus,n,t} + \beta_{Walking\_Time} Walking\_Time^{Acc}_{Bus,n,t} + \beta_{Cost,n} Cost^{Acc}_{Bus,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Bus,n} \tag{51}$$

$$V'^{Acc}_{Jitney,n,t} = \alpha_{Jitney} + \beta_{IVTT\_BusSer} IVTT^{Acc}_{Jitney,n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Acc}_{Jitney,n,t} + \beta_{Walking\_Time} Walking\_Time^{Acc}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Acc}_{Jitney,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Jitney,n} \tag{52}$$

$$V'^{Acc}_{Ride(Pri),n,t} = \alpha_{Ride(Pri)} + \beta_{IVTT\_Ride} IVTT^{Acc}_{Ride(Pri),n,t}$$
$$+ \beta_{Waiting\_Time} Waiting\_Time^{Acc}_{Ride(Pri),n,t}$$
$$+ \beta_{Cost,n} Cost^{Acc}_{Ride(Pri),n,t} + \beta_{Flex\_Ride} Flexible_n \tag{53}$$
$$+ \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Pri),n}$$

$$V'^{Acc}_{Ride(Sha),n,t} = \alpha_{Ride(Sha)} + \beta_{IVTT\_Ride} IVTT^{Acc}_{Ride(Sha),n,t}$$
$$+ \beta_{Waiting\_Time} Waiting\_Time^{Acc}_{Ride(Sha),n,t}$$
$$+ \beta_{Cost,n} Cost^{Acc}_{Ride(Sha),n,t} + \beta_{Flex\_Ride} Flexible_n \tag{54}$$
$$+ \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Sha),n}$$

$$V'^{Egr}_{Walk,n,t} = \alpha_{Walk} + \beta_{Walking\_Time} Walking\_Time^{Egr}_{Walk,n,t} + \omega_{Walk,n} \tag{55}$$

$$V'^{Egr}_{Bus,n,t} = \alpha_{Bus} + \beta_{IVTT\_BusSer} IVTT^{Egr}_{Bus,n,t}$$
$$+ \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Bus,n,t}$$
$$+ \beta_{Walking\_Time} Walking\_Time^{Egr}_{Bus,n,t} + \beta_{Cost,n} Cost^{Egr}_{Bus,n,t} \tag{56}$$
$$+ \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Bus,n}$$

$$V'^{Egr}_{Jitney,n,t} = \alpha_{Jitney} + \beta_{IVTT\_BusSer} IVTT^{Egr}_{Jitney,n,t}$$
$$+ \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Jitney,n,t}$$
$$+ \beta_{Walking\_Time} Walking\_Time^{Egr}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Egr}_{Jitney,n,t} \tag{57}$$
$$+ \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Jitney,n}$$

$$V'^{Egr}_{Ride(Pri),n,t} = \alpha_{Ride(Pri)} + \beta_{IVTT\_Ride} IVTT^{Egr}_{Ride(Pri),n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Ride(Pri),n,t} + \beta_{Cost,n} Cost^{Egr}_{Ride(Pri),n,t} + \beta_{Flex\_Ride} Flexible_n + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Pri),n} \tag{58}$$

$$V'^{Egr}_{Ride(Sha),n,t} = \alpha_{Ride(Sha)} + \beta_{IVTT\_Ride} IVTT^{Egr}_{Ride(Sha),n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Ride(Sha),n,t} + \beta_{Cost,n} Cost^{Egr}_{Ride(Sha),n,t} + \beta_{Flex\_Ride} Flexible_n + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Sha),n} \tag{59}$$

Explanatory variables are the same as those of approach II and can be seen in Table 11.

4.6.3. Model Development

Several approaches were tested before adopting the final three shown above. Models with a constant IVTT coefficient were estimated in addition to models with market segmentation based on trip distance and models with piecewise linear time coefficients before concluding that interacting time with the logarithm of trip distance yields the best overall fit. Random time coefficients were also tried but yielded very complex and computationally burdensome models due to the large number of time variables. As such, the cost coefficient was the only random variable which results in a distributed value of time. Models with combined OVTT were also estimated but results showed that distinguishing waiting time from walking time led to a better model fit.

Socio-economic variables of interest were mainly identified through the descriptive analysis. Some variables showed high correlation with choices but were found to be not significant (gender, educational level) which might be attributed to the small sample size. These were eliminated from the final model. Outlier analysis was also performed to improve the model. Choice probabilities were predicted for all observations in the sample and those below 0.01 (around 5% of all observations) were filtered and analyzed. Characteristics of the outliers were compared to those of the remaining sample in the aim of identifying additional variables that can improve prediction for these observations. The outliers showed no significant divergence from the rest of the sample and no further data points were eliminated. In fact, the low probabilities can be attributed to the fact that the probability of using the BRT is divided over 30 different alternatives which results in low probabilities for each alternative.

Latent variables were also explored based on indicators in section 5 of the survey. Hybrid choice models, which include latent variables, are widely used in discrete choice models as they represent behaviorally the unobserved heterogeneity across individuals resulting from different perceptions and attitudes (Walker and Ben-Akiva, 2002). However, these models resulted in estimation issues due to the large number of variables and parameters involved. A larger sample may be required for such specifications, especially since the number of alternatives is large. Therefore, latent variables were excluded from the final models.

CHAPTER 5

RESULTS

After defining the model specific to the case study, this chapter presents the estimation results for the three approaches before selecting the preferred model based on selection criteria discussed in chapter 3. The selected model will be analyzed and used for policy analysis. Section 5.1 provides the estimation results for the three approaches defined in chapter 4. Section 5.2 presents the procedure adopted for selecting the best model, before performing stability analysis and discussing findings from the model in section 5.3. Section 5.4 focuses on forecasting and testing the variation of BRT and ridesourcing ridership under different policy scenarios.

5.1. Model Estimation Results

PythonBiogeme version 2.6a was used for model estimation (Bierlaire, 2016) with the simulated likelihood maximized through Monte-Carlo integration with "MLHS" draws which are well suited for discrete choice models (Bierlaire, 2015). Model estimation was performed for the three defined approaches, in addition to several other specifications that were out-performed by the aforementioned approaches or eliminated for statistical significance considerations. Two thousand draws were used for estimation as most level-of-service variables stabilized at this stage, with further stability analysis performed later on after selecting a final model. Estimation results and model statistics are provided in Table 12.

Table 12: Estimation Results and Model Statistics for All Three Approaches

	Approach 1		Approach 2		Approach 3	
Variable/Parameter	**Parameter Estimate**	**p-value**	**Parameter Estimate**	**p-value**	**Parameter Estimate**	**p-value**
α_{Bus}	-0.0966	0.95	-0.34	0.74	-0.479	0.80
$\alpha_{Park\,\&\,Ride}$	2.78	0.04	1.61	0.12	1.63	0.40
$\alpha_{Ride(Pri)}$	0.724	0.61	0.672	0.6	0.599	0.74
$\alpha_{Ride(Sha)}$	2.49	0.06	2.80	0.01	2.82	0.13
α_{Jitney}	0.0232	0.99	-0.188	0.87	-0.381	0.84
α_{Walk}	1.21	0.38	1.33	0.22	1.17	0.54
Car IVTT/ln(distance) (h/ln(km))	-	-	-5.55	0.1	-6.29	0.06
IVTT BRT (h)	-	-	-2.28	0.54	-3.71	0.21
IVTT Feeders (h)	-	-	-2.32	0.22	-	-
IVTT Bus/Jitney (h)	-	-	-	-	-2.55	0.19
IVTT Ridesourcing (h)	-	-	-	-	-3.58	0.09
Waiting Time (h)	-	-	-14.40	0.00	-14.1	0.00
Walking Time (h)	-	-	-7.05	0.00	-7.61	0.00
Car Travel Time/ln(distance) (h/ln(km))	-6.31	0.04	-	-	-	-
BRT Travel Time (h)	-1.99	0.43	-	-	-	-
Feeders Travel Time (h)	-6.24	0.00	-	-	-	-
$\mu_{\beta_{Cost,n}}$	-0.844	0.00	-0.754	0.01	-0.761	0.06
$\sigma_{\beta_{Cost,n}}$	0.803	0.00	0.734	0.03	-0.703	0.20
Flexibility (specific to car)	3.18	0.04	4.43	0.02	3.88	0.00
Flexibility (specific to ridesourcing)	-1.59	0.01	-0.994	0.05	-1.05	0.02
PT User (specific to car)	-5.40	0.01	-4.61	0.02	-5.7	0.00
PT User (specific to bus & jitney)	0.894	0.03	1.42	0.00	1.36	0.00
Ridesourcing User (specific to ridesourcing)	1.38	0.05	1.48	0.00	-3.58	0.09

Table 12 (Cont.): Estimation Results and Model Statistics for All Three Approaches

	Approach 1		Approach 2		Approach 3	
Variable/Parameter	**Parameter Estimate**	**p-value**	**Parameter Estimate**	**p-value**	**Parameter Estimate**	**p-value**
Age (specific to car, in years)	0.267	0.088	0.288	0.00	0.258	0.00
Age (specific to ridesourcing, in years)	-0.0278	0.00946	-0.0305	0.15	-0.0372	0.03
$\boldsymbol{\sigma}_{\omega_{Bus}}$	1.52	0.00	1.27	0.00	1.09	0.00
$\boldsymbol{\sigma}_{\omega_{Park}}$	3.22	0.00	3.63	0.00	3.05	0.00
$\boldsymbol{\sigma}_{\omega_{Ride(Pri)}}$	0.939	0.08	1.56	0.00	1.65	0.00
$\boldsymbol{\sigma}_{\omega_{Ride(Sha)}}$	0.625	0.25	0.889	0.05	1.13	0.00
$\boldsymbol{\sigma}_{\omega_{Jitney}}$	2.38	0.00	-2.55	0.00	2.2	0.00
$\boldsymbol{\sigma}_{\omega_{Walk}}$	2.68	0.00	2.51	0.00	2.75	0.00
$\boldsymbol{\sigma}_{\omega_{Car}}$	8.12	0.00	8.91	0.00	9.36	0.00
L(0)	-3,833.52		-3,833.52		-3,833.52	
L($\hat{\beta}$)	-1,186.611		-1,170.814		-1,170.264	
ρ^2	0.690		0.694		0.694	
$\bar{\rho}^2$	0.685		0.686		0.686	
AIC	2,423.223		2,397.629		2,398.528	
BIC	2,549.969		2,539.585		2,545.555	
Final Gradient	+9.083E-05		+7.526E-06		+7.962E-05	

5.2. Model Selection

In this section, a model out of the three estimated ones will be selected based on criteria defined in section 3.2. Accordingly, signs of the parameters and significance of the variables will be assessed alongside the goodness of fit of the models, value of time analysis, and cross validation tests before adopting a final model.

5.2.1. Signs of the Parameters and Significance of the Variables

The signs of the estimated level-of-service coefficients were consistent with expectations as travel time and cost coefficients were all negative for the three estimated models which implies that an increment in any time or cost component decreases the utility of the corresponding travel mode. However, some significance issues exist for the travel time of the BRT and feeders. For the first model which combines IVTT and OVTT, all variables are significant at the 5% level except for the BRT travel time. When IVTT and OVTT are separated, the waiting and walking time variables were highly significant, and their coefficients diverged substantially from the estimated coefficients of IVTT which implies that the model with separated time components is superior and allows better interpretation. However, significance issues remain for the BRT's IVTT, and to a lesser extent that of feeders. However, these level of service variables cannot be eliminated due to their integral role in the choice process. Model 3 is slightly preferable as the coefficient for ridesourcing IVTT becomes significant at the 10% level after splitting feeders, but the BRT's IVTT coefficient remains not significant even though its p-value decreased compared to model 2 implying higher significance.

Significance concerns are also faced for the constants and variance of shared ridesourcing's error component, while only significant socio-economic parameters were kept in the final models.

5.2.2. Goodness of Fit

Goodness of fit is usually an essential criterion for model selection. Since the same data set was used to estimate all models, the rho-square and final log-likelihood can be used for comparison. The Akaike and Bayesian Information Criteria will also be assessed for model selection as shown in Table 13.

Table 13: Goodness of Fit Measures

	Model 1	Model 2	Model 3
L(0)	-3,833.520	-3,833.520	-3,833.520
$L(\hat{\boldsymbol{\beta}})$	-1,186.611	-1,170.814	-1,170.264
$\bar{\boldsymbol{\rho}}^2$	0.685	0.686	0.686
AIC	2,423.223	2,397.629	2,398.528
BIC	2,549.969	2,539.585	2,545.555

The final log-likelihood and adjusted rho-squared show that separating in-vehicle travel time from out-of-vehicle travel time improves the model. The AIC Criterion reflects a slight advantage to model 2 characterized by a unified coefficient for feeders' IVTT as it has the lowest AIC value, thus the best overall fit. Models 2 and 3 remain better than model 1 which further supports that separating travel time components is beneficial while using different coefficients for feeders results in an over-fitted model. The BIC criterion, which penalizes additional parameters more than the AIC criterion, shows an increased preference towards model 2 as model 3 is further penalized for its additional coefficient.

Overall, goodness of fit measures reveal that model 2 is the best fit for the data. Separating IVTT and OVTT strengthens the predictive power of the model, but a further segregation of IVTT coefficients based on feeder type results in an over-fitted model.

5.2.3. Value of Time Analysis

Value of time is of paramount interest in model analysis because it is heavily relied on for pricing and monetization of benefits in travel time savings. Accordingly, resulting values of time from different models are assessed for the different modeling approaches before adopting the preferred model. Since the cost coefficient is random with log-normal distribution, the values of time were computed through Monte Carlo simulation for 1,000 observations. A distribution of the value of time is obtained and the average, median, and range are reported.

Table 14: Value of Time Analysis (L.L./h) for the 3 Different Models

		Car*	BRT	Feeders	Bus/Jitney	Ridesourcing	Waiting	Walking
Model 1	Average	19,439	6,137	19,242	-	-	-	-
	Median	14,368	4,533	14,213	-	-	-	-
	Min	814	257	805	-	-	-	-
	Max	137,237	43,281	135,714	-	-	-	-
Model 2	Average	15,624	6,344	6,455	-	-	40,068	19,617
	Median	12,429	4,989	5,077	-	-	31,512	15,428
	Min	963	364	370	-	-	2,299	1,125
	Max	102,304	43,173	43,931	-	-	272,673	133,496
Model 3	Average	17,491	9,369	-	6,440	9,041	35,609	19,219
	Median	13,412	7,556	-	5,193	7,291	28,716	15,498
	Min	1,315	497	-	342	480	1,890	1,020
	Max	217,595	72,970	-	50,155	70,413	277,326	149,677

*** VOT*ln(distance) is reported for Car, where distance is the door-to-door travel distance**

The analysis shows that for model 1, the VOT for feeders is over three times that of the BRT which seems excessive. Models 2 and 3 show relatively close values of time; however, model 3 shows lower value of time for bus and jitney compared to the BRT which contradicts with literature findings to be discussed later in section 5.3. Models 2 and 3 also show that commuters are more sensitive to OVTT compared to IVTT which is also consistent with previous findings from other studies (e.g.: Danaf et al., 2019). Model 3 seems the best overall as it provides similar results to model 2 while allowing more flexibility for feeders.

5.2.4. Cross Validation Prediction Test

A 5-fold cross validation test was also performed before selection as a measure of predictive power of the model. The data set was divided into 5 sub-sets where 4 are used for estimation and one for prediction. The 5 possible combinations of subsets are all tested and results are shown in Table 15.

Table 15: 5-Fold Cross Validation Test Results

	Model 1	**Model 2**	**Model 3**
$\mathbf{L_1(\hat{\beta})}$	-315.064	-302.757	-299.466
$\mathbf{L_2(\hat{\beta})}$	-310.456	-312.941	-303.140
$\mathbf{L_3(\hat{\beta})}$	-371.070	-377.268	-374.523
$\mathbf{L_4(\hat{\beta})}$	-294.042	-291.807	-289.338
$\mathbf{L_5(\hat{\beta})}$	-390.956	-392.544	-385.549
Sum	-1681.589	-1677.316	-1652.016

The cross-validation test shows that model 3 yields the lowest log-likelihood and has thus the best ability to predict the observed choices. Thus, relaxing the constraint of equal IVTT sensitivity for all feeders allows for better mode choice prediction and as such, model 3 is the most desirable for this purpose.

5.2.5. Conclusion

Overall, it is clear that model 1 is inferior to the other two and will be thus eliminated. Models 2 and 3 are close both in specification and in performance, with model 3 being slightly over-fitted with additional parameters but allowing for better choice prediction and enhanced analysis, especially when it comes to comparing different feeders. Accordingly, model 3 will be selected for these purposes, especially as it is preferable to have separate ridesourcing coefficients as the new service is of main interest in the study.

5.3. Findings and Analysis

After selecting model 3, estimation was repeated at different starting points and at a higher number of draws to validate the stability and robustness of the estimated parameters. Stability was reached at 25,000 draws after the number of draws was progressively increased by increments of 5,000. Stability is assumed to be reached when all estimated parameters, except alternative specific constants, vary by less than 10% in absolute value compared to the results from the previous estimation exercise.

After fixing the number of draws, the starting values of the parameters were changed progressively to test the robustness of the estimation results as different starting values might lead to different local maxima of the log-likelihood function. The estimation results were found to be robust with changes in estimated coefficients persisting below 10% for different initial values. Estimation results for the final and stable model are shown in Table 16.

Table 16: Estimation Results for the Final Model (R= 25,000 draws)

Variable/Parameter	Parameter Estimate	Robust Standard Error	Robust t-test	p-value
α_{Bus}	0.0583	1.67	0.03	0.97
$\alpha_{Park\,\&\,Ride}$	2.16	1.59	1.36	0.17
$\alpha_{Ride(Pri)}$	1.07	1.69	0.64	0.52
$\alpha_{Ride(Sha)}$	3.33	1.54	2.16	0.03
α_{Jitney}	0.146	1.58	0.09	0.93
α_{Walk}	1.96	1.73	1.13	0.26
Car IVTT/ln(distance) (h/ln(km))	-5.75	3.47	-1.66	0.10
IVTT BRT (h)	-2.30	2.71	-0.85	0.40
IVTT Bus/Jitney (h)	-2.25	1.66	-1.36	0.17
IVTT Ridesourcing (h)	-3.37	1.97	-1.71	0.09
Waiting Time (h)	-14.50	3.11	-4.65	0.00
Walking Time (h)	-7.37	2.06	-3.58	0.00
$\mu_{\beta_{Cost,n}}$	-0.721	0.218	-3.31	0.00
$\sigma_{\beta_{Cost,n}}$	0.664	0.147	4.5	0.00
Flexibility (specific to car)	4.79	1.82	2.63	0.01

Table 16 (Cont.): Estimation Results for the Final Model (R= 25,000 draws)

Variable/Parameter	Parameter Estimate	Robust Standard Error	Robust t-test	p-value
Flexibility (specific to ridesourcing)	-1.03	0.494	-2.08	0.04
PT User (specific to car)	-5.07	1.88	-2.7	0.01
PT User (specific to bus & jitney)	1.34	0.43	3.13	0.00
Ridesourcing User (specific to ridesourcing)	1.31	0.492	2.66	0.01
Age (specific to car, in years)	0.305	0.0888	3.43	0.00
Age (specific to ridesourcing, in years)	-0.0308	0.0184	-1.67	0.09
$\boldsymbol{\sigma}_{\boldsymbol{\omega}_{Bus}}$	1.24	0.43	-2.89	0.00
$\boldsymbol{\sigma}_{\boldsymbol{\omega}_{Park}}$	3.20	0.637	-5.02	0.00
$\boldsymbol{\sigma}_{\boldsymbol{\omega}_{Ride(Pri)}}$	1.70	0.466	-3.65	0.00
$\boldsymbol{\sigma}_{\boldsymbol{\omega}_{Ride(Sha)}}$	0.989	0.338	-2.93	0.00
$\boldsymbol{\sigma}_{\boldsymbol{\omega}_{Jitney}}$	2.55	0.451	-5.65	0.00
$\boldsymbol{\sigma}_{\boldsymbol{\omega}_{Walk}}$	2.56	0.447	-5.72	0.00
$\boldsymbol{\sigma}_{\boldsymbol{\omega}_{Car}}$	9.46	1.76	-5.36	0.00

Initial Log-Likelihood: -3,833.52
Final Log-Likelihood: -1170.043
Rho-Squared: 0.694
Adjusted Rho-Squared: 0.686
Akaike Information Criterion: 2,398.086
Bayesian Information Criterion: 2,545.112
Final Gradient Norm: +8.914E-05

All estimated level-of-service variables carry negative signs as anticipated. The standard deviation of the cost coefficient is highly significant which indicates significant taste heterogeneity across individuals and supports the log-normal specification. The marginal utility of car is always negative but decreases in magnitude as the door-to-door travel distance increases. This implies that a congested 20 km trip that takes 40 min is more burdensome than a longer trip that requires similar travel time due to better traffic conditions. This makes the BRT more attractive over congested corridors where large delays inflate the in-vehicle travel time, and less attractive over lightly congested corridors where longer distances can be commuted at the same travel time. The marginal disutility of car IVTT is also lower for long trips compared to shorter ones and the non-linear decrease over distance is illustrated in Figure 14.

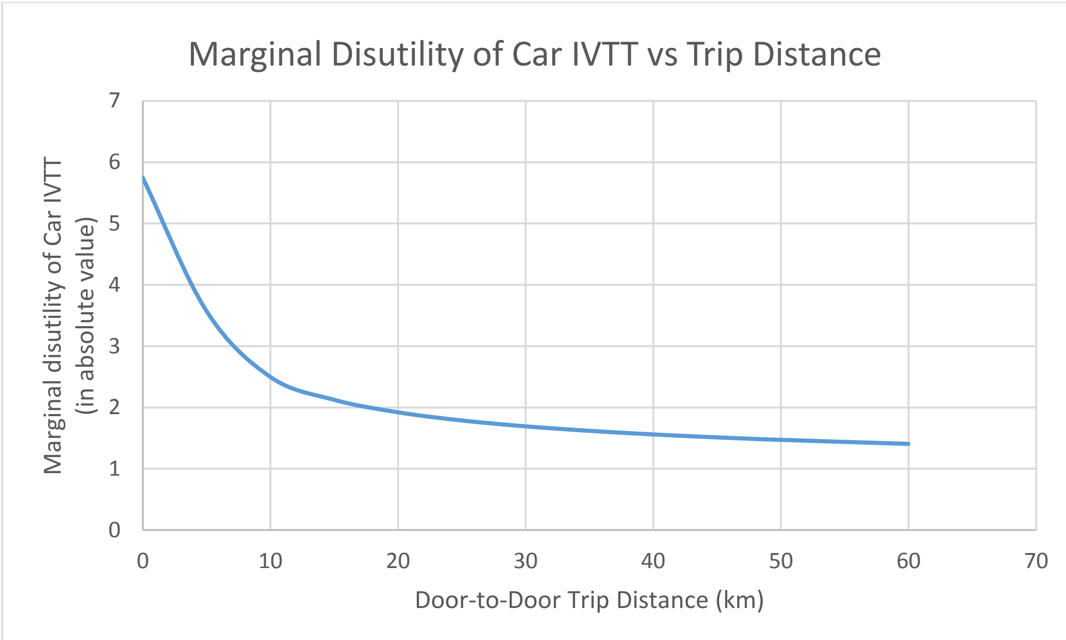

Figure 14: Variation in Marginal Disutility of Car IVTT as a Function of Trip Distance

As distance increases, the coefficient becomes more flat implying that the effect of distance is reduced for longer trips. It must be noted that the variation is very steep for trips below 10 km. However, this is not a concern for the study as very short trips are excluded from the study as dictated by the study area and screening criteria. In fact, few trips are below 10 km with the shortest door-to-door trip being around 7 km.

Sensitivities for BRT and traditional feeders' IVTT are relatively similar. As for ridesourcing, the marginal disutility of IVTT is higher for feeders than for the main mode which is consistent with the literature (Yap et al., 2016; Arentze and Molin, 2013). This implies that extending the transit corridor and reducing connecting trips result in a better quality of service if other factors are held constant. Commuters are also more sensitive to ridesourcing IVTT compared to traditional feeders. This suggests that ridesourcing has more potential for short feeder trips and can be explained by an implicit belief of users that the service's pricing algorithm reflects travel duration. The coefficients of out-of-vehicle travel time components are significantly more negative than those of in-vehicle travel time, indicating an intuitive additional burden for walking and waiting times. Commuters are found to be more sensitive to waiting time than walking time which is consistent with Arentze and Molin's conclusions for the egress stage (2013) but not for the remaining legs. These results also contradict with Yap et al.'s findings (2016) which reveal more sensitivity to walking time. This can be attributed to an established perception in the Lebanese market of unreliable waiting times due to the current state of operating public transportation.

The computed values of time will not be deterministic as imposed by the specification of the cost coefficient, and will accordingly be computed through simulation. In the case of the car, the VOT is also systematically dependent on the logarithm of the total trip distance. Monte Carlo simulation of 1,000 instances indicates that the average car value of time is $VOT_{Car}^{Avg} = \frac{15{,}539}{\ln(distance)}$. This translates to around 6,744 L.L./h for a 10-km trip which is higher than the values of 3,928 LB/h (in year 2010 L.L.) found by Danaf et al. (2014), and 5,500 L.L. found by IBI Group and TEAM (2009). Inflation and socio-economic differences are factors to consider before comparing the values of time for different years. Beyond car users, values of time were also derived for the BRT and its feeders with average values obtained in the order of 6,212 L.L./h for the BRT, 6,077 L.L./h for bus and jitney, and 9,101 L.L./h for ridesourcing. Values of time are robust and consistent with results obtained from the model estimated with 2,000 draws. Only the BRT's VOT changed significantly as its coefficient is not highly significant and was thus less robust to changes in the number of draws. Traditional feeders have values of time similar to that of the BRT while that of ridesourcing exceeds the main mode's VOT by 46.5%. Hensher et al. (2006) found through their evaluation of possible public transportation investments in Sydney that value of time for access is almost the same as that of the main mode, while for egress modes the value of time exceeds that of the main mode by 61.8%. As for walking and waiting time, their respective average values of time are 19,904 L.L./h and 39,160 L.L./h and are significantly above that of in-vehicle travel time, which is consistent with findings from Danaf et al. (2019) who find that non-motorized and out-of-vehicle travel time have VOTs that exceed that of public transportation IVTT by 97.7% and 54.4% respectively based on an application in the Greater Boston Area.

Table 17: Values of Time for the Final Model

Value of Time (L.L./h)				
	Average	Median	Minimum	Maximum
Car	$\frac{15{,}539}{\ln(distance^*)}$	$\frac{12{,}394}{\ln(distance^*)}$	$\frac{1{,}455}{\ln(distance^*)}$	$\frac{161{,}895}{\ln(distance^*)}$
Car (10 km)	6,744	5,382	632	70,310
Car (25 km)	4,824	3,850	452	50,296
Car (40 km)	4,210	3,360	395	43,887
BRT	6,212	4,957	582	64,758
Bus/Jitney	6,077	4,850	569	63,350
Ridesourcing	9,101	7,264	853	94,885
Waiting	39,160	31,253	3,670	408,258
Walking	19,904	15,885	1,865	207,508

Moving to socio-economics, the age coefficients reveal that older commuters are more inclined towards car commutes, while younger travelers are more likely to embrace ridesourcing which is similar to literature findings (Alemi et al., 2018; Young and Farber, 2019). The positive sign of the flexibility coefficient specific to car reflects higher car preference for users with flexible work/study arrangements since they can afford some delays imposed by congestion without disrupting their tasks. As for ridesourcing, the flexibility coefficient becomes negative implying that ridesourcing is perceived as a more reliable travel alternative when commuters wants to reach their destination on time. Frequent public transportation users are more likely to use the BRT and even more in favor of traditional feeders like the bus and jitney. This is in line with expectations as commuters already using such modes are supposedly more in favor of them and are likely to adopt them as feeders when using the BRT. Last but not least, commuters who have previously used ridesourcing are more likely to embrace it for the feeder trips as reflected by the positive sign of the corresponding coefficient. This implies that users of ridesourcing are satisfied with the service, and that awareness campaigns and progressively increasing reach and familiarity will drive more people into using ridesourcing for access and egress trips.

5.4. Forecasting and Policy Analysis

The selected model will be calibrated then used for forecasting and policy analysis. An origin-destination matrix for vehicle trips in Lebanon was obtained from SETS International for the AM peak in year 2012. As the zonal configuration was not fully compatible with the proposed study area, some zones were merged while others divided and the gravity model[3] used to obtain the desired sub-matrix. Moreover, a 2% yearly traffic growth is assumed similarly to the rate used in the BRT pre-feasibility report (World Bank, 2015), an average vehicle occupancy rate of 1.2 (MoE/UNDP/GEF, 2015), and a car share of 80% of total vehicular trips (IBI Group and TEAM International, 2009). The resulting matrix is for car passenger trips which

[3] Trips were distributed proportionally to the ratio of the population of the origin zone to the square of the travel distance between the origin and destination.

is compatible with our analysis. Demand is forecasted for the year 2019 which is when the current study data was collected. It would be preferable to forecast for the year of the BRT launch but that date is not officially announced.

5.4.1. Calibration of the Constants

One concern is that the model was estimated using SP data and cannot be used for forecasting unless alternative specific constants are re-calibrated based on observed market shares (Ben-Akiva et al., 2019; Cherchi and de Dios Ortúzar, 2006). SP data provides better insights than RP on the trade-offs in the decision making process, but will rarely reproduce true market shares which is problematic in ridership forecasting and necessitates calibration. Coefficients of level-of-service and socio-economic variables are not changed, unless the model scale is varied, to maintain the trade-off that is well captured by SP data. Constants on the other hand reflect choice shares across the sample rather than the population as attributes and levels presented in SP data are not always consistent with real alternatives. Accordingly, by calibrating the constants, the analyst can present a model that reproduces observed market shares while retaining the enhanced trade-offs across variables ensured by SP analysis (Hensher et al., 2005).

Calibration is challenging when revealed preference data is not available, which is the case in this study as the BRT is not yet operational. However, actual market shares for bus and jitney are available (though not solely as access or egress modes), while other BRT studies performed ridership forecasting and can be used as reference for comparison. As such, calibration of the constants will be performed to reproduce the observed ratio of bus to jitney trips similarly to Glerum et al. (2013), a BRT share close to that from other forecasting studies, and a realistic target for ridesourcing market share in the absence of the true share (Liu et al., 2019). This is performed over three different steps:

- Step 1: Calibration of the bus or jitney constants to maintain the actual ratio of their shares.
- Step 2: Calibration of the constants of all feeders to reproduce the expected market share of the BRT in the study area as obtained from other studies.
- Step 3: Calibration of the constants of ridesourcing to make sure that its overall market share is realistic.

Steps 1 and 2 are performed on a base model without ridesourcing as other studies do not include ridesourcing in the analysis of feeders. In this model, coefficients are assigned their estimated values without any modification, while base values of the attributes are defined to reflect real market values as further detailed in Appendix B. After step 2, ridesourcing is added to the feeders and then its constants are calibrated to yield a market share that is realistic based on findings in other markets. A final check is then performed to make sure that the final calibrated model verifies the three constraints.

IBI Group and TEAM International (2009) estimate that during the AM peak, taxis and jitney are responsible for 6% of trips in Beirut, while buses and vans cover 12.6%. The ratio of bus to jitney trips is assumed to hold for feeders of the BRT and calibration in step 1 is performed to reach a ratio of bus to jitney trips that is around 2. As for the BRT share, Khatib & Alami and TMS Consult were hired to conduct a BRT traffic modelling report in the year 2017. The latter study forecasts at the launch year a BRT share of 25% from all vehicle trips moving from northern Mount Lebanon into Beirut, compared to a 60% share for cars and 15% for other public transportation modes. Since our study only involves car and BRT as modes of main transport, other modes are eliminated. The ratio of car trips to BRT trips is assumed to hold which translates after extrapolation into a share of 70.59% for the car and 29.41% for the BRT. Thus, constants specific to feeder modes are calibrated based on this BRT share in step 2. Ridesourcing is then added and the estimated constants are used without any modification at first. After forecasting accordingly, the ridesourcing market share is calibrated to reach the desired target by varying the constants of private and shared ridesourcing simultaneously. While ridesourcing's share of total trips in San Francisco reaches 15% during weekday peaks (Castiglioni et al., 2017), its share in most urban cities is closer to 5% (Schaller, 2018). In counties around city cores, shares fall to between 1% and 3%, while in dense city centers the share increases significantly and reaches 6.9% and 7.7% in Washington DC and Boston respectively (Fehr & Peers, 2019). Market share in Beirut is not available, but given international experience to date, we set an endogenous target of 0 to 5% for ridesourcing's share of total vehicle trips in our study area as a higher share is not to be expected at the launch of the BRT.

We start by forecasting market shares using the estimated constants and parameters while eliminating ridesourcing from the choice sets of all respondents which yields a BRT share of 32.79% and a ratio of bus to jitney trips equaling 0.81. As we don't know the true market shares of the travel modes once the BRT becomes operational, the method suggested by Train (2009) cannot be used, and a grid search approach is adopted for calibration (Liu et al., 2019). To reach the desired ratio of bus to jitney trips, the constant of jitney is lowered rather than increasing that of the bus as the share of the BRT needs to be reduced overall. Table 18 shows results for the ratio of bus to jitney trips and the overall BRT share for different values of the jitney constant.

Table 18: Jitney Constant and Resulting Ratio of Bus to Jitney Trips and BRT Share

α_{Jitney}	Ratio of Bus to Jitney Trips	BRT Share
0.146	0.81	32.79%
-0.5	1.19	32.21%
-1	1.59	31.91%
-1.5	2.11	31.68%

Results from Table 18 reveal that a jitney constant of -1.5 leads to shares that better reflect the actual market. The BRT share in that case is 31.68% which is within 10% of the share found in the BRT Traffic Modelling report. As such, no calibration for the BRT share is performed as the mentioned study does not involve calibration against real market shares, and since obtained results are close, we stick to our value.

Next, ridesourcing is added as an additional feeder and the grid search approach is applied again to reach a market share that falls within the target range of 0 to 5% of overall trips. Table 19 summarizes calibration results. The shares of total trips using any form of ridesourcing for access and for egress are separately computed, and their average is then computed and adopted as ridesourcing share.

Table 19: Ridesourcing Constants and the Corresponding Calibration Results

$(\alpha_{\text{Ride(Pri)}}, \alpha_{\text{Ride(Sha)}})$	Ridesourcing Share	Ratio of Bus to Jitney Trips	BRT Share
(1.07, 3.33)	8.08%	2.09	34.85%
(0.5, 2.5)	6.68%	2.07	34.28%
(0, 2)	4.85%	2.05	33.53%

All three calibration targets are verified in the final model which will therefore be adopted for forecasting and policy analysis.

5.4.2. Policy Analysis

Using the calibrated constants obtained in section 5.4.1, the base market shares for this study are forecasted. The sample enumeration method is used with the appropriate weights assigned based on the origin-destination matrix and computed as the ratio of the number of total trips observed from the O-D matrix to the number of observations in the sample commuting between the same endpoints. The base case levels are defined based on existing travel time and costs for car and other travel modes, in addition to the expected fare and speed of the BRT as suggested by the BRT Traffic Modelling report. Appendix B provides further details on base values definition. The base case scenario serves as a benchmark for comparison to test the impacts of different policies of interest on the overall market shares of diverse modes. The base market shares are summarized in Table 20.

Table 20: Forecasting Results for Base Conditions using the Calibrated Model

Main Mode	**Number of Peak Hour Person Trips**	**Percentage of Total Trips in the Peak Hour**	
Car	9,546	66.47%	
BRT	4,816	33.53%	
Access Mode	**Number of Peak Hour Person Trips**	**Percentage of Total Trips**	**Percentage of BRT Trips**
Park & Ride	1,314	9.15%	27.29%
Walk	2,722	18.95%	56.51%
Bus	224	1.56%	4.65%
Jitney	114	0.80%	2.37%
Ridesourcing (Private)	62	0.43%	1.28%
Ridesourcing (Shared)	380	2.65%	7.90%
Ridesourcing (Total)	442	3.08%	9.18%

Table 20 (Cont.): Forecasting Results for Base Conditions using the Calibrated Model

Egress Mode	Number of Peak Hour Person Trips	Percentage of Total Trips	Percentage of BRT Trips
Walk	2,696	18.77%	55.97%
Bus	789	5.49%	16.37%
Jitney	380	2.65%	7.89%
Ridesourcing (Private)	139	0.97%	2.88%
Ridesourcing (Shared)	813	5.66%	16.88%
Ridesourcing (Total)	952	6.63%	19.76%

14,362 total trips are projected to occur during the peak hour out of which the BRT is expected to serve over 4,800. When ridesourcing was added, the BRT market share increased from 31.68% to 33.53% reflecting possible synergies between the two modes. This indicates that the introduction of ridesourcing increases the number of potential BRT users by enlarging the catchment area, serving regions where other public transportation modes are deficient, serving market segments that favor the flexibility and rewards of the new service, or other reasons. In the following sub-sections, market shares are forecasted for different policies of interest.

Park and ride is expected to be a popular access mode with 27.29% of BRT users projected to rely on the service to reach transit stations. This translates to over 1,300 commuters, or roughly 1,000 parking spaces assuming a vehicle occupancy of around 1.3. That is only during the peak hour, meaning that the provided capacity should be even higher to serve all demand. While the existing BRT studies do not mention the estimated park and ride at launch, they state that capacity is expected to be limited. As such, a policy will be dedicated to testing different levels of park and ride capacity in order to assess its impact on BRT ridership.

Walking is expected to be the most popular feeder with around 56% of BRT trips involving it for access and egress trips. That share is high but reasonable as population density in coastal zones, which are adjacent to the BRT, is much higher than farther zones, meaning that walking to the BRT is valid for a large portion of the population.

As the study investigates the interaction between ridesourcing and mass transit, several scenarios will be dedicated to testing this relation. Adding ridesourcing already revealed that it can induce additional demand for the BRT. Further policies involve varying ridesourcing price to get insights on its impact on BRT ridership and understand the potential of possible collaborations between transit authorities and ridesourcing companies. Price reductions can be achieved through subsidies or when the additional ridesourcing demand and optimal fleet utilization resulting on dense feeder lines can justify lower fares while maintaining the desired profit margins.

Moreover, policy makers are mainly interested in enhancing BRT ridership; thus, scenarios will test policies that can drive commuters towards transit by improving the attractiveness of BRT alternatives or decreasing that of the car. Policies that involve higher car parking prices at the destination should deter commuters from driving and their impact will be tested through different parking price surges. This can be practically achieved by taxing private parking operators and eliminating free curb-side and public parking.

Improving feeders is another driver for higher BRT ridership and one form can be tested by reducing bus headways, especially as commuters were highly sensitive to waiting time. Transit authorities can achieve lower headways by increasing the number of feeder buses and such investment should be justified before adoption.

The impact of limited availability of park and ride is also tested as the capacity of such facilities is expected to be restricted. Lastly, an optimal BRT ridership scenario is performed in which ridesourcing fare is decreased by 50%, car parking price is increased by 50%, and park and ride is kept at full capacity simultaneously. This scenario provides insights on the maximum BRT ridership that can be expected. Table 21 summarizes the scenarios that will be tested in the following sub-sections.

Table 21: Description of Forecasting Scenarios

Scenario	Policy	Variation Range	Base Values for Trips between Zones 2 and A
1	Reduction in Ridesourcing Fares	0% to -50%	5,000 L.L. and 3,000 L.L. for private and shared ridesourcing respectively (same for access and egress)
2	Increase in Car Parking Prices at Destination	0% to 50%	7,000 L.L.
3	Reduction in Feeder Bus Headway	0% to -50%	10 min (Access), 6 min (Egress)
4	Limited Park and Ride Availability	100% to 25%	100% (unconstrained availability)
5	Hybrid Scenario	50% reduction in ridesourcing fare, 50% increase in car parking price, 100% park and ride capacity	Same as 4 previous scenarios

5.4.2.1. Scenario 1: Reduction in Ridesourcing Fare

In the first scenario, the fare of ridesourcing is progressively decreased to assess its incremental impact on overall market share. This approach raises the utility of alternatives involving ridesourcing which can benefit the BRT. However, this comes at a cost to transit authorities or ridesourcing companies depending on who is covering the price reduction. As such, this scenario provides insights on whether a subsidy or collaboration with ridesourcing companies can be justified. Table 22 provides forecasting results for all modes under different ridesourcing fares that range from the base fare to its half with progressive decrements of 10%.

Table 22: Forecasting Results for Different Levels of Ridesourcing Fare

	Percentage Change in Ridesourcing Fare					
	0% (Base)	**-10%**	**-20%**	**-30%**	**-40%**	**-50%**
	Percentage of Total Trips					
Main Mode						
Car	66.47%	66.08%	65.58%	64.91%	64.07%	63.11%
BRT	33.53%	33.92%	34.42%	35.09%	35.93%	36.89%
Access Mode						
Park & Ride	9.15%	9.28%	9.49%	9.82%	10.33%	11.01%
Walk	18.95%	18.59%	18.17%	17.68%	17.13%	16.56%
Bus	1.56%	1.50%	1.43%	1.34%	1.26%	1.19%
Jitney	0.80%	0.77%	0.75%	0.73%	0.72%	0.71%
Ridesourcing (Private)	0.43%	0.57%	0.76%	1.01%	1.30%	1.64%
Ridesourcing (Shared)	2.65%	3.21%	3.83%	4.51%	5.19%	5.78%
Ridesourcing (Total)	3.08%	3.78%	4.59%	5.51%	6.48%	7.42%
Egress Mode						
Walk	18.77%	18.26%	17.66%	16.99%	16.29%	15.59%
Bus	5.49%	5.06%	4.59%	4.11%	3.64%	3.22%
Jitney	2.65%	2.47%	2.27%	2.04%	1.83%	1.67%
Ridesourcing (Private)	0.97%	1.24%	1.58%	2.02%	2.56%	3.18%
Ridesourcing (Shared)	5.66%	6.89%	8.33%	9.92%	11.61%	13.23%
Ridesourcing (Total)	6.63%	8.12%	9.91%	11.94%	14.17%	16.41%

The applied fare reductions increased market shares for both the BRT and ridesourcing which indicates that a possible collaboration can be beneficial for both parties involved. As the ridesourcing fare is decreased by half, demand for this service more than doubled implying that overall revenues should increase despite the lower fare. Revenue management techniques and cost optimization offer an opportunity to ridesourcing companies to benefit from the proposed policy, in addition to an embellished public image and a higher number of regular users. As for BRT authorities, a half-reduced ridesourcing fare at the feeder stages is expected to augment BRT demand by 3.36% as its market share increases from 33.53% to 36.89%. Arrangements for such integration can include clauses related to data sharing which benefits transit authorities as ridesourcing companies archive their data neatly compared to traditional public transportation modes. Moreover, ridesourcing can replace low usage buses and cover low density areas which bodes well for social equity. The increased BRT share can also reduce traffic congestion and greenhouse gas emissions though such conclusions require further analysis.

As ridesourcing fare is further decreased, demand for both the BRT and ridesourcing rises exponentially, which implies that a policy involving ridesourcing fare reductions is mainly effective for large price drops. Under such policies, ridesourcing companies can sustain part of the fare reduction, while transit authorities subsidize the remaining part or offer other benefits to collaborating on-demand mobility providers. Figure 15 illustrates the share of the BRT and ridesourcing at the access and egress stages under all investigated price levels.

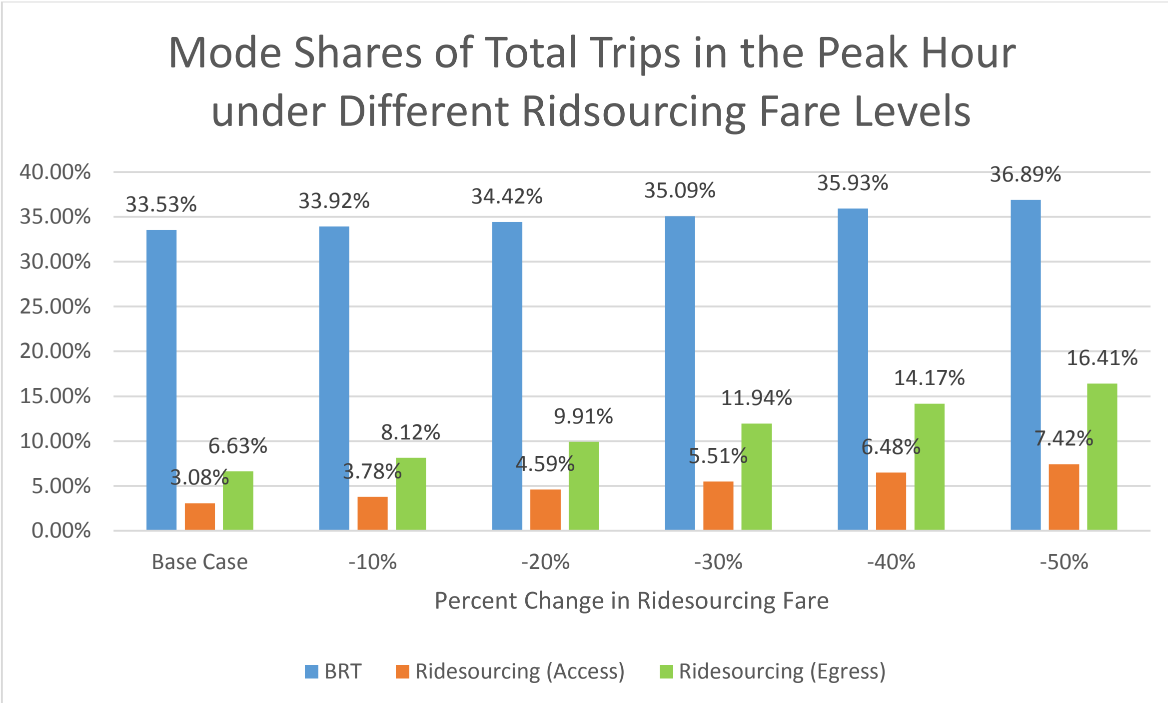

Figure 15: Summary of Forecasting Results for Different Levels of Ridesourcing Fares

5.4.2.2. Scenario 2: Increase in Car Parking Prices at Destination

This scenario penalizes the utility of the car alternative by gradually increasing car parking prices at trip destination and assessing the resulting switching rate to the BRT. Park & ride rates are maintained at the base level as these facilities are expected to be jointly priced with the BRT and an increase in their parking price will hurt the BRT. Table 23 summarizes forecasting results for car parking prices increasing from 0% to 50% (10% increments).

Table 23: Forecasting Results for Different Levels of Car Parking Prices

	Percentage Change in Car Parking Price					
	0% (Base)	**+10%**	**+20%**	**+30%**	**+40%**	**+50%**
	Percentage of Total Trips					
Main Mode						
Car	66.47%	65.63%	64.78%	63.90%	62.97%	61.95%
BRT	33.53%	34.37%	35.22%	36.10%	37.03%	38.05%
Access Mode						
Park & Ride	9.15%	9.46%	9.79%	10.14%	10.52%	10.91%
Walk	18.95%	19.31%	19.65%	19.97%	20.28%	20.57%
Bus	1.56%	1.62%	1.68%	1.75%	1.85%	2.01%
Jitney	0.80%	0.82%	0.84%	0.88%	0.92%	0.99%
Ridesourcing (Private)	0.43%	0.44%	0.46%	0.47%	0.48%	0.49%
Ridesourcing (Shared)	2.65%	2.72%	2.80%	2.89%	2.98%	3.08%
Ridesourcing (Total)	3.08%	3.17%	3.26%	3.36%	3.46%	3.57%
Egress Mode						
Walk	18.77%	19.09%	19.37%	19.62%	19.87%	20.14%
Bus	5.49%	5.72%	5.98%	6.25%	6.55%	6.91%
Jitney	2.65%	2.72%	2.79%	2.88%	2.98%	3.09%
Ridesourcing (Private)	0.97%	0.99%	1.02%	1.05%	1.09%	1.12%
Ridesourcing (Shared)	5.66%	5.85%	6.06%	6.29%	6.54%	6.80%
Ridesourcing (Total)	6.63%	6.84%	7.08%	7.35%	7.63%	7.92%

For every 10% additional increment in car parking prices, BRT ridership rises by around 0.9% on average based on the forecasting range. This policy is effective as it incurs no extra costs on transit authorities, while diverting car users to public transportation reduces the burden on infrastructure and the environmental footprint of the transport industry. This policy can be achieved by imposing high taxes on private parking operators, higher fares for public parking, and by eliminating free curb-side parking, with such policies being more possible when transit alternatives are provided compared to the status-quo where transit options are limited and flawed. Figure 16 displays the shares of BRT and ridesourcing from total vehicle trips under different car parking prices.

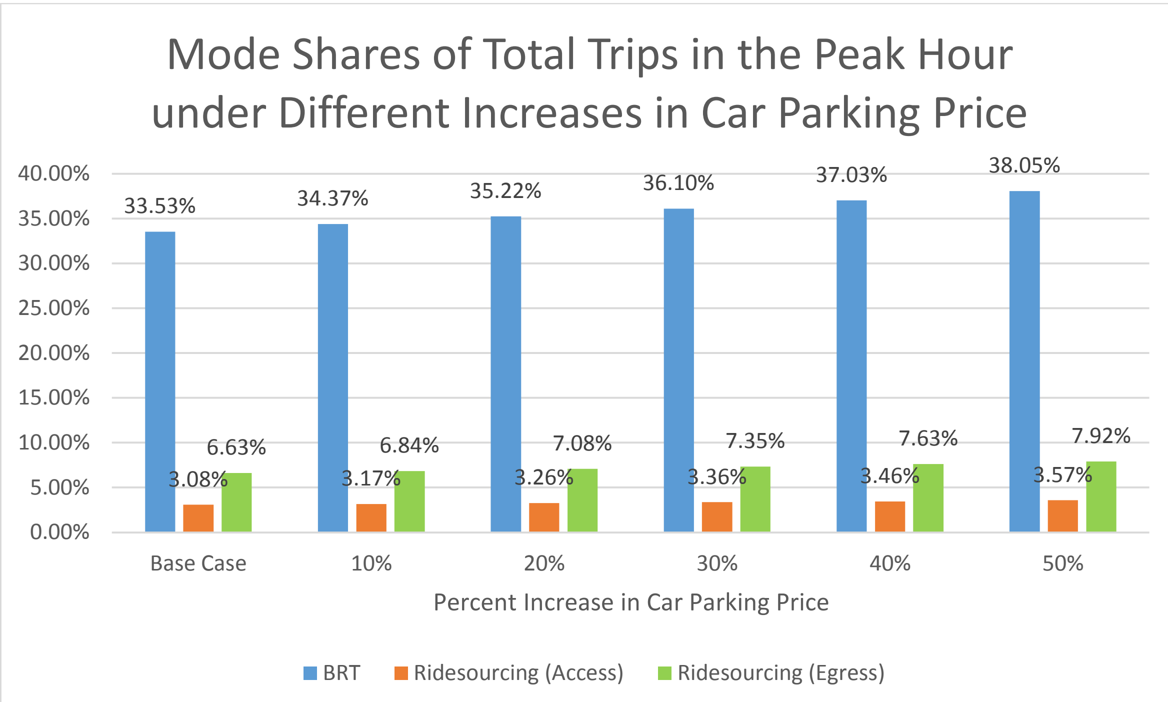

Figure 16: Summary of Forecasting Results for Different Levels of Car Parking Prices

5.4.2.3. Scenario 3: Reduction in Feeder Bus Headway

It was noticed that traditional public transportation modes had relatively low shares across feeders compared to park & ride, walking, and ridesourcing. While jitney operations are not usually coordinated and headways are sporadic, feeder buses are expected to operate on defined schedules. This scenario tests the impact of enhancing feeder bus service by reducing their headway which decreases waiting time. This policy requires investments in a higher number of feeder buses and higher operating costs but can be effective as commuters were found to be highly sensitive to waiting time. Table 24 presents market shares for different feeder bus headways starting with the base value and reaching a decrease of 50% through successive decrements of 10%.

Table 24: Forecasting Results for Different Levels of Feeder Bus Headways

	Percentage Change in Bus Headway					
	0% (Base)	**-10%**	**-20%**	**-30%**	**-40%**	**-50%**
	Percentage of Total Trips					
Main Mode						
Car	66.47%	66.35%	66.23%	66.10%	65.96%	65.80%
BRT	33.53%	33.65%	33.77%	33.90%	34.04%	34.20%
Access Mode						
Park & Ride	9.15%	9.15%	9.15%	9.15%	9.15%	9.15%
Walk	18.95%	18.89%	18.82%	18.73%	18.64%	18.52%
Bus	1.56%	1.76%	1.98%	2.22%	2.49%	2.78%
Jitney	0.80%	0.79%	0.79%	0.79%	0.79%	0.79%
Ridesourcing (Private)	0.43%	0.43%	0.42%	0.42%	0.41%	0.41%
Ridesourcing (Shared)	2.65%	2.63%	2.61%	2.59%	2.57%	2.55%
Ridesourcing (Total)	3.08%	3.05%	3.03%	3.00%	2.98%	2.95%
Egress Mode						
Walk	18.77%	18.68%	18.57%	18.46%	18.32%	18.17%
Bus	5.49%	5.86%	6.25%	6.67%	7.11%	7.58%
Jitney	2.65%	2.61%	2.57%	2.53%	2.49%	2.46%
Ridesourcing (Private)	0.97%	0.95%	0.93%	0.91%	0.89%	0.87%
Ridesourcing (Shared)	5.66%	5.55%	5.44%	5.33%	5.22%	5.11%
Ridesourcing (Total)	6.63%	6.50%	6.37%	6.24%	6.11%	5.99%

While the impact of this policy on feeder bus ridership is noteworthy, its effect on BRT ridership is minimal as its market share increased only by 0.67% for a 50% reduction in headway. This policy seems not very effective overall as the main goal in this case would be to maximize BRT ridership rather than feeder bus ridership unless the concern is about traffic on local roads. The implementation of this policy requires investing in more feeder buses and operating additional trips. It seems more effective to allocate such funds to subsidies on ridesourcing or other BRT improvement as their impacts are expected to be more positive on BRT ridership. Figure 17 shows market shares for the BRT, ridesourcing, and buses for different variations of feeder bus headways.

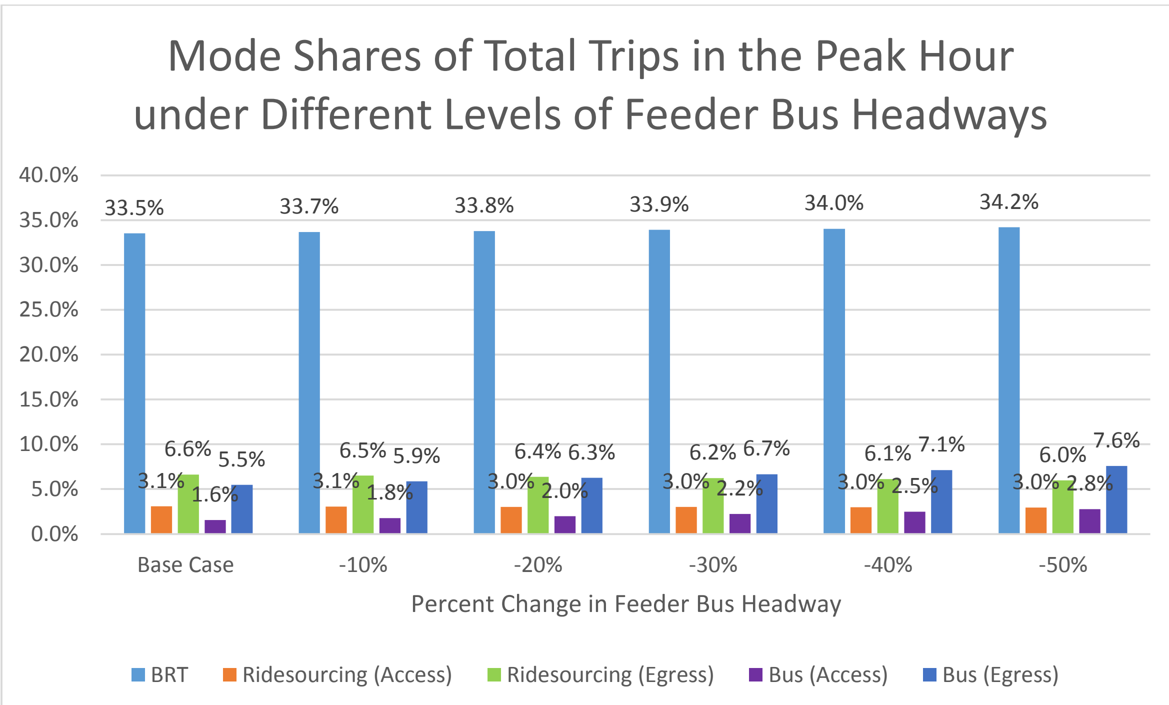

Figure 17: Summary of Forecasting Results for Different Levels of Feeder Bus Headways

5.4.2.4. Scenario 4: Limited Park & Ride Availability

Park & ride was found to be a popular access mode in the base scenario. While current designs do not include the exact layout and capacity of park & ride facilities, it is expected that capacity will be limited and not able to satisfy full demand. Therefore, this scenario is considered to assess the impact of limited park and ride availability on overall BRT ridership. Park and ride availability levels of 25%, 50%, and 75% are simulated, alongside the base case where availability is not constrained, and results are summarized in Table 25. Simulation is performed to assign the availability of park and ride alternatives for different sample observations. A random number is simulated from a U(0,1) distribution and availability is assigned for the corresponding respondent based on the desired availability level.

Table 25: Forecasting Results for Different Park and Ride Availability Levels

	Share of the Population for which Park & Ride is Available			
	100% (Base)	**75%**	**50%**	**25%**
	Percentage of Total Trips			
Main Mode				
Car	66.47%	67.36%	68.21%	69.04%
BRT	33.53%	32.64%	31.79%	30.96%
Access Mode				
Park & Ride	9.15%	6.26%	4.23%	2.00%
Walk	18.95%	19.87%	20.70%	21.60%
Bus	1.56%	1.79%	1.96%	2.12%
Jitney	0.80%	1.15%	1.17%	1.23%
Ridesourcing (Private)	0.43%	0.47%	0.50%	0.52%
Ridesourcing (Shared)	2.65%	3.09%	3.23%	3.48%
Ridesourcing (Total)	3.08%	3.56%	3.73%	4.00%
Egress Mode				
Walk	18.77%	18.37%	18.19%	17.94%
Bus	5.49%	5.23%	5.10%	4.77%
Jitney	2.65%	2.55%	2.45%	2.39%
Ridesourcing (Private)	0.97%	0.96%	0.85%	0.84%
Ridesourcing (Shared)	5.66%	5.53%	5.21%	5.02%
Ridesourcing (Total)	6.63%	6.49%	6.05%	5.86%

Limited park and ride availability is negatively affecting BRT ridership. Reductions in BRT share are significant with around 0.85% of overall prospective customers lost for every 25% reduction in park and ride availability. A park and ride availability for 25% of total expected demand reduces the share of the BRT from 33.53% to 30.96%. As such, transit authorities should put efforts to meet demand for park and ride as this feeder mode can cater for over a quarter of BRT customers and over 9% of overall vehicle trips. Existing public parking nearby stations and curb-side parking on adjacent roads should be dedicated to BRT riders, while further parking spaces could be developed if feasible and justified. Resulting modal shares from different park and ride capacity levels are plotted in Figure 18.

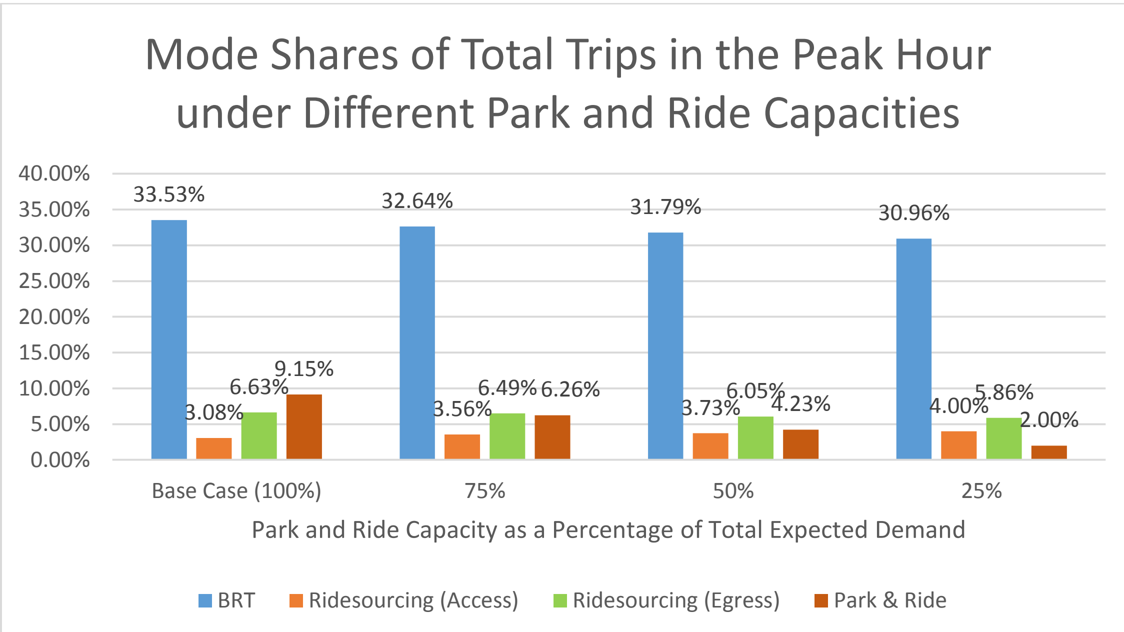

Figure 18: Summary of Forecasting Results for Different Park and Ride Capacity Levels

5.4.2.5. Scenario 5: Hybrid Scenario

This scenario combines car parking price surges and ridesourcing fare reductions simultaneously to yield a higher BRT market share. This policy provides insights on optimistic ridership levels that can be expected for the BRT at launch. In this scenario, ridesourcing fare is reduced by 50% and car parking price is increased by 50%. Results are summarized in Table 26.

Table 26: Forecasting Results for Optimal BRT Ridership

Main Mode	Number of Peak Hour Person Trips	Percentage of Total Trips in the Peak Hour	
Car	8,401	58.50%	
BRT	5,961	41.50%	
Access Mode	**Number of Peak Hour Person Trips**	**Percentage of Total Trips**	**Percentage of BRT Trips**
Park & Ride	1,875	13.06%	31.46%
Walk	2,520	17.54%	42.27%
Bus	203	1.42%	3.41%
Jitney	123	0.85%	2.06%
Ridesourcing (Private)	261	1.81%	4.37%
Ridesourcing (Shared)	979	6.82%	16.43%
Ridesourcing (Total)	1,240	8.63%	20.80%
Egress Mode	**Number of Peak Hour Person Trips**	**Percentage of Total Trips**	**Percentage of BRT Trips**
Walk	2,357	16.41%	39.54%
Bus	537	3.74%	9.00%
Jitney	270	1.88%	4.54%
Ridesourcing (Private)	515	3.59%	8.65%
Ridesourcing (Shared)	2,282	15.89%	38.28%
Ridesourcing (Total)	2,797	19.48%	46.93%

Forecasting results reveal that BRT ridership can reach around 6,000 passengers during the peak hour under the mentioned conditions. This corresponds to 41.50% of all motorized trips compared to 33.53% under base conditions which implies that combining multiple policies can attract higher BRT ridership. As such, the BRT lane is expected to serve over 5,000 car users during the peak hour which is higher than the number of car passengers that a highway lane can serve under a low vehicle occupancy of around 1.2, meaning that the introduction of the BRT might reduce the severity of congestion at the northern entrance to Beirut.

5.4.2.6. Summary

Overall, BRT ridership is expected to fall in the 30% to 42% range. Car users are highly sensitive to parking prices, and increased fares can drive a large portion to switch to the BRT. When it comes to feeders, investments are best allocated to ridesourcing and park and ride facilities as improvements in these services are expected to be most beneficial to the BRT. Reductions in the headways of feeder buses seem to reap minimal gains and thus do not justify large investments when the objective is to maximize BRT ridership.

CHAPTER 6

CONCLUSION

This chapter concludes the thesis by summarizing findings and contributions, stating research limitations, and providing recommendations for future research.

6.1. Summary of Findings

This research provides a framework to model demand for ridesourcing when integrated with high capacity transit systems while considering all stages of a multi-modal transit trip: access, main travel, and egress simultaneously. A mixed logit model was developed with an error component structure to capture correlation in unobserved factors across alternatives involving similar access, main travel, or egress modes. The systematic utilities and error components are specific to a mode and stage and are later combined to yield the utilities of alternatives when these are multi-modal. This approach allows to quantify the relative impact of level of service variables at different trip stages on the overall selection process, and gives a clear overview of the impact of feeders on mass transit ridership.

The thesis tests the complementarity between mass transit and ridesourcing, as the latter service is quickly gaining traction in cities all over the globe. The framework can be easily extended to accommodate other emerging mobility technologies whether as main modes or as a feeder. The proposed framework was applied to the planned Beirut BRT based on survey data collected from a well-defined study area. The case study provides practical insights on the integration problem.

The model suggests that ridesourcing is popular with young commuters and those with inflexible schedules implying a higher perceived travel time reliability of ridesourcing among commuters compared to traditional public transportation modes like bus and jitney. Previous on-demand mobility users were more eager to embrace the ridesourcing service for access and egress reflecting customer satisfaction and potential increase in market share as general commuters become more keen about and aware of the new service.

Forecasting was also performed using the developed model for the analysis of 4 policies that aim to augment BRT ridership and quantify the impact of ridesourcing on the transit system's popularity. Results reveal that ridesourcing and park and ride widen the target customers of the BRT and help it reach higher ridership levels. The introduction of ridesourcing as a feeder augmented the overall market share of the BRT from 31.68% to 33.53%. BRT demand was found to be highly sensitive to ridesourcing fare demonstrating that a partnership between mass transit and on-demand mobility can succeed. BRT share increases from 33.53% to 36.89% when the fare is reduced by half. Enhancing park and ride capacity brings high gains to BRT ridership, while increasing the frequency of feeder buses has a minor positive effect of the transit system. Car parking rates also had a major impact on BRT ridership and a price surge reduces the appeal of private cars and drives commuters towards the BRT. Overall, improving coverage and diversifying feeders to satisfy all tastes is beneficial to high capacity transit systems.

6.2. Research Contributions

This thesis advances the existing literature on ridesourcing integration with mass transit at methodological and practical levels. The developed framework fits all stages of multi-modal trips and allows the choice between such trips and uni-modal ones without constraining mode selection at any stage. Most studies on the first-mile-last-mile problem from the demand side tackle access and egress stages separately while constraining the other. Moreover, the framework can accommodate any emerging or traditional travel mode at the access, main travel, or egress stage which allows for flexible choice modeling that can simultaneously and efficiently incorporate a wide range of travel alternatives. The mixed logit with error components structure can be easily expanded to accommodate all travel modes available in a certain context in addition to any planned or suggested future mode which is very convenient in first-mile-last-mile problems.

At a practical level, the impact of ridesourcing on transit ridership is emerging as a major topic in transportation research, with different studies leading to contradictory results and no general consensus yet reached. This study contributes towards clarifying the ambiguous relation and is a step forward towards building a robust understanding of the relation between mass transit and on-demand mobility services. To our knowledge, this is the first paper that conducts demand modeling for ridesourcing at both access and egress stages of a mass transit system in the full context of an urban city and its suburbs. Furthermore, the case study of Lebanon explores attitudes towards ridesourcing in developing countries which is rarely tackled in the existing literature. The study provides insights on such service in contexts where public transportation is deficient and awareness for emerging mobility services is limited. The application also complements studies by local authorities on the BRT with further analysis of ridership levels and possible feeders' deficiencies. The policy analysis further provides guidelines for better regulation and implementation of the proposed transit system.

6.3. Research Limitations

The main limitation in the study is the lack of initial market shares to use for re-calibration of the model before forecasting, as the BRT is not yet operational. Furthermore, the origin-destination matrix used in forecasting was not fully compatible with the study area and assumptions had to be made before deriving a practical sub-matrix. Another drawback is the limited sample size used in the survey. With variables defined at the trip stage level and multiple alternatives possible through diverse mode combinations, high accuracy in model estimation requires a large sample. Several variables were left out as they turned out to be not significant despite clear trends observed in the descriptive analysis which might be attributed to a small number of observations due to the limited sample. Moreover, the layout of the experimental design does not allow testing the impact of monthly or yearly BRT subscriptions and rather remains at the level of a single trip. The research was also restricted to current car users to reduce the number of alternatives while a broader analysis should address users of all modes.

Further limitations include the assumption that ridesourcing is accessible to all individuals while it should be practically limited to smartphone users. The analysis involving reduction in ridesourcing fares is not based on supply and demand interaction, with the number of drivers and vehicles assumed to vary in accordance with demand levels. No spatial analysis was performed for feeder buses and jitneys and these were assumed to be reachable to all commuters, while in fact, bus and jitney lines do not cover all road networks. The spatial location of park and ride facilities was not taken into account when computing access travel time since the exact locations of these facilities are not yet clearly defined.

6.4. Recommendations for Future Research

Future research should address the limitations of the current study and build further beyond it. For the case study, models can be developed to include ridesourcing, and/or other modes, for main travel to assess the potential of ridesourcing for door-to-door travel and identify possible competitive trends with fixed alignment transit systems such as the BRT. The study can also be performed with a larger sample to incorporate more variables and improve significance of coefficients such as the BRT's in-vehicle travel time. From a modeling perspective, latent variables can be added to the model, especially for emerging technologies or modes of transport, as attitudes and perceptions towards new mobility concepts might play a key role in the selection process. Future disruptive technologies like autonomous vehicles can also be included due to their large potential for providing transportation services.

Further analysis can investigate correlations across error components. The study assumes that the error terms are independent, while in fact, some modes might have correlations in unobserved factors. A more detailed model can test the magnitude and statistical significance of the correlations across error terms. Sequential estimation can also be performed separately for access, egress, and main mode before comparing findings and forecasting results to those obtained from simultaneous estimation.

Methodologically, future research can build an enhanced experimental design that allows fare integration for selected multi-modal trips. An interesting approach would be to study the complementarity of mass transit and ridesourcing in the context of Mobility-as-a-Service (MaaS) as these services are starting to gain traction in multiple cities. When fare integration is adopted, studies on fare splitting across stakeholders can also be performed as it is paramount to the implementation and success of such collaboration.

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APPENDIX A: FULL QUESTIONNAIRE

Ridesourcing and Bus Rapid Transit Feeders in Lebanon

Survey Description and Consent Form

Hello, my name is [INTERVIEWER'S NAME] from [FIRM'S NAME]. I am contacting you on behalf of researchers at the American College of Beirut. This research study is being conducted by the Civil Engineering Department to study travel preferences in Lebanon and perception towards new transportation modes and mass transit systems. Participants of this research are directly approached by the survey firm to do the interview. Around four hundred participants will take part in this study. The results of this research will be used by researchers and policy makers to suggest improved transportation services in the future.

Your participation should take approximately 30 minutes. Please understand that your participation is completely voluntary: you have the right to choose not to participate or to withdraw anytime without having to give any reason for your withdrawal. Refusal or withdrawal from the study will involve no loss of benefits to which you are otherwise entitled nor will it affect your relationship with AUB or AUBMC. You receive no direct benefits from participating in this research; however, your participation does help researchers better understand the potential of new mobility concepts in Lebanon. Your participation in this study does not involve any physical or emotional risk to you beyond the risks of daily life.

Participation in this study is completely confidential. Your name or any other identifying information will not be asked. Your individual privacy and the confidentiality of the information you provide will be maintained in all published and written data analysis resulting from the study. A copy of the consent form will be kept with you for further reference.

The collected data from this survey will be stored for a minimum of 3 years on the computer of the principal investigator and the research assistant who will both have access to it. The interview will not be audio recorded.

If you have questions about your rights as a participant, you can contact the AUB Social and Behavioral IRB office at: 01-350000 ext. 5454/5455; and if you have questions about the research study you can contact:

Professor Maya Abou Zeid

Civil and Environmental Engineering

ma202@aub.edu.lb

[NOTE TO INTERVIEWER: ASK TO SPEAK TO THE ADULT WHOSE BIRTHDAY WAS LAST. IF HE/SHE IS NOT AVAILABLE, PICK THE ADULT WITH THE PRIOR BIRTHDAY, ETC… IF NO ADULT IS AVAILABLE AT THE TIME OF THE VISIT, COME BACK AT ANOTHER TIME.]

Do you voluntarily consent to participate in this survey?

1. Yes
2. No

[NOTE TO INTERVIEWER: IF YES, PROCEED WITH INTERVIEW AND GIVE THE PARTICIPANT A COPY OF THE CONSENT FORM. IF NO, THANK RESPONDENT AND TERMINATE THE INTERVIEW.]

[NOTE TO INTERVIEWER: THE NEXT QUESTION ABOUT THE RESPONDENT'S ADDRESS SHOULD BE RECORDED BY THE INTERVIEWER AT THE START OF THE INTERVIEW.]

I. Where is the respondent's residence located?

1. Zone 1 (Jbeil Caza)
2. Zone 2 (Tabarja, Safra, Ghedras)
3. Zone 3 (Jounieh, Kaslik, Jeita)
4. Zone 4 (Kesserwan caza excluding zones 2 and 3)
5. Zone 5 (Bikfaya, Bharsaf, Dhour Choueir)
6. Zone 6 (Dbayeh, Aoukar, Haret El Bellan)
7. Zone 7 (Rabieh, Raboueh, Ain Aar)
8. Zone 8 (Naccache, Tellel Srour, Antelias, Haret El Ghouarneh)
9. Zone 9 (Jal El Deeb, Zalka, Deir Salib)

Section 1: Screening Criteria

We will first ask you a few questions to determine whether you are eligible to participate in this survey.

1. **Which of the following categories best describes your main occupational status? (If you work and study simultaneously, please select the place you go to more often and consider it for the rest of the survey)**
    1. Full-time worker (≥ 30 hours/week)
    2. Part-time worker (< 30 hours/week)
    3. Full-time student
    4. Part-time student
    5. Retired
    6. Unemployed
    7. Other

[NOTE TO INTERVIEWER: IF THE ANSWER IS “5”, “6”, or “7”, THANK RESPONDENT AND ASK TO SPEAK TO THE NEXT ADULT HOUSEHOLD MEMBER WHOSE BIRTHDAY WAS LAST.]

1b. How many cars are available to your household (including company cars)?

1. 0
2. 1
3. 2
4. 3
5. 4
6. 5+

[NOTE TO INTERVIEWER: IF THE ANSWER IS “0”, THANK RESPONDENT AND END THE INTERVIEW]

2. **How do you commute to work/college most of the time? If you use more than one mode, please select the mode you use for the longest distance.**
    1. Drive private car (alone)
    2. Drive private car with other passengers on board
    3. Dropped off (family member, friend, colleague, etc.)
    4. Service
    5. Bus/minibus
    6. Uber/Careem (or similar app-based services)
    7. Taxi
    8. Motorcycle
    9. Walking all the way from residence to work.
    10. Other [Please specify:____]

[NOTE TO INTERVIEWER: IF “1” OR “2” OR “3”, PROCEED TO QUESTION 3. OTHERWISE, THANK RESPONDENT AND SPEAK TO THE NEXT ADULT HOUSEHOLD MEMBER WHOSE BIRTHDAY WAS LAST.]

3. **Where is your work place/college located?**

1. Municipal Beirut
2. Suburban area within Greater Beirut
3. Outside greater Beirut

[NOTE TO INTERVIEWER: IF THE ANSWER IS “Outside greater Beirut”, THANK RESPONDENT AND ASK TO SPEAK TO THE NEXT ADULT HOUSEHOLD MEMBER WHOSE BIRTHDAY WAS LAST.]

[NOTE TO INTERVIEWER: ACCORDING TO THE RESPONDENT’S CHOICE, ASK HIM/HER TO CHOOSE THE SPECIFIC AREA FROM BELOW.]

[NOTE TO INTERVIEWER: IF THE ANSWER TO QUESTION I (ABOUT RESIDENCE) IS “a”, “b”, OR “c”, PROCEED TO QUESTION 3.1. OTHERWISE, SKIP QUESTION 3.1 AND MOVE TO QUESTION 3.2]

3.1 Please select the specific area of your work/college:

Municipal Beirut

1. Port
2. Mar Mikhael, Khodr
3. Geitawi, Karm el-Zeitoun
4. Gemmayzeh, Saifi, Remeil, Tabaris
5. Nasra, Furn al-Hayek, Monot, Sodeco
6. Achrafieh, Mar Mitr, Sassine
7. Sioufi, Aadlieh, Hotel Dieu
8. Ras al-Nabaa, Mathaf, Badaro
9. Horsh, Qasqas, Chatila
10. Tareek al-Jdideh, Fakhani
11. Mazraa, Bourj Abi Haidar
12. Basta Faouka, Basta Tahta
13. Baladieh, Maarad, Riad al-Solh
14. Serail, Minet al-Hosn
15. Ain Mreisseh, al-Zarif
16. Hamra, Wardieh
17. AUB/IC campuses
18. Manara, Jal al-Bahr
19. Rawcheh, Qoreitem
20. Snoubra, Munla, Verdun
21. Moussaitbeh, Zaidanieh, Batrakieh
22. Tallet al-Khayat, Wata
23. UNESCO, Ramlet al-Baida
24. Mar Elias, Dar Mouallimee

Suburban area within Greater Beirut

25. Bourj Hammoud (North), Dora
26. Bourj Hammoud (South), Nabaa
27. Sin el-Fil
28. Jisr al-Bacha
29. Furn al-Chebbak, Ain al-Roummaneh
30. Chiyah
31. Ghobeiry, Haret Hreik
32. Hazmieh, Fayadieh, Baabda
33. Hadath, Laylakeh
34. Bouchrieh
35. Jdeideh, Sid Bouchrieh
36. Dekwaneh, Mkalles
37. Dbayeh, Aoukar, Haret El Bellan
38. Rabieh, Raboueh, Ain Aar
39. Naccache, Tellel Srour
40. Antelias, Haret El Ghouraneh
41. Jal El Deeb
42. Other

[NOTE TO INTERVIEWER: IF THE ANSWER IS "Other", THANK RESPONDENT AND ASK TO SPEAK TO THE NEXT ADULT HOUSEHOLD MEMBER WHOSE BIRTHDAY WAS LAST.]

3.2 Please select the specific area of your work/college:

Municipal Beirut

1. Port
2. Mar Mikhael, Khodr
3. Geitawi, Karm el-Zeitoun
4. Gemmayzeh, Saifi, Remeil, Tabaris
5. Nasra, Furn al-Hayek, Monot, Sodeco
6. Achrafieh, Mar Mitr, Sassine
7. Sioufi, Aadlieh, Hotel Dieu
8. Ras al-Nabaa, Mathaf, Badaro
9. Horsh, Qasqas, Chatila
10. Tareek al-Jdideh, Fakhani
11. Mazraa, Bourj Abi Haidar
12. Basta Faouka, Basta Tahta
13. Baladieh, Maarad, Riad al-Solh
14. Serail, Minet al-Hosn
15. Ain Mreisseh, al-Zarif
16. Hamra, Wardieh
17. AUB/IC campuses
18. Manara, Jal al-Bahr
19. Rawcheh, Qoreitem
20. Snoubra, Munla, Verdun
21. Moussaitbeh, Zaidanieh, Batrakieh
22. Tallet al-Khayat, Wata
23. UNESCO, Ramlet al-Baida
24. Mar Elias, Dar Mouallimee

Suburban area within Greater Beirut

25. Bourj Hammoud (North), Dora
26. Bourj Hammoud (South), Nabaa
27. Sin el-Fil
28. Jisr al-Bacha
29. Furn al-Chebbak, Ain al-Roummaneh
30. Chiyah
31. Ghobeiry, Haret Hreik
32. Hazmieh, Fayadieh, Baabda
33. Hadath, Laylakeh
34. Bouchrieh
35. Jdeideh, Sid Bouchrieh
36. Dekwaneh, Mkalles
37. Other

[NOTE TO INTERVIEWER: IF THE ANSWER IS “Other”, THANK RESPONDENT AND ASK TO SPEAK TO THE NEXT ADULT HOUSEHOLD MEMBER WHOSE BIRTHDAY WAS LAST]

4. **Does your work/college trip involve driving on the coastal highway or any parallel road to the highway (sea side road, etc.) for more than 3 km?**
    1. Yes
    2. No

[NOTE TO INTERVIEWER: IF THE ANSWER IS “No”, THANK RESPONDENT AND ASK TO SPEAK TO THE NEXT ADULT HOUSEHOLD MEMBER WHOSE BIRTHDAY WAS LAST.]

Section 2: Characteristics of Different Travel Modes

In this section, we will ask you about your use of public transportation and its availability in the vicinity of your residence.

5. **During the last 12 months, how often did you use public transportation in Lebanon (bus, minibus, service, …) for any purpose?**
    1. More than once a week
    2. About once a week
    3. Few times a month (2-3 times)
    4. About once a month
    5. Several times a year
    6. About once or twice a year
    7. Never

Section 3: Attributes of Commute to Work

In this section, we will ask you about your current trip to work.

10. Taking all things together, how satisfied are you with your commute to work/college by car?

1. Very Dissatisfied
2. Dissatisfied
3. Neither satisfied nor dissatisfied
4. Satisfied
5. Very Satisfied

[NOTE TO INTERVIEWER: IF THE ANSWER TO QUESTION 2 IS “3”, SKIP QUESTION 11 AND GO TO QUESTION 12.]

11. Do you usually pick up/drop off somebody (children, wife/husband, friend, etc.) on your way to or from work/college?

1. Yes, pick-up only on the way back home
2. Yes, drop-off only on the way to work/college
3. Yes, pick-up and drop-off on the way to work/college and on the way back home
4. No

12. What is your most typical door-to-door travel time from home to work/college by car?

1. Less than 30 minutes
2. From 30 to 44 minutes
3. From 45 to 59 minutes
4. From 59 to 74 minutes
5. From 75 to 89 minutes
6. From 90 to 104 minutes
7. From 105 to 119 minutes
8. 120 minutes or more

[NOTE TO INTERVIEWER: IF THE ANSWER TO QUESTION 2 IS “3”, SKIP QUESTIONS 14 TO 18 AND MOVE DIRECTLY TO QUESTION 19.]

14. Do you pay for parking?

1. Yes, I pay from my own pocket.
2. Yes, but the company reimburses/pays parking fees
3. No

[NOTE TO INTERVIEWER: IF THE ANSWER TO QUESTION 14 IS “3”, SKIP QUESTION 15 AND MOVE DIRECTLY TO QUESTION 16.]

15. Where/How do you park your car?

1. On street (park meters)
2. Valet parking

3. At company/college grounds
4. Private parking lot (on a daily basis)
5. Private parking lot (monthly subscription)

[NOTE TO INTERVIEWER: IF ANSWER TO QUESTION 15 IS “1” or “2” or “4”, GO TO QUESTION 17 AND SKIP QUESTION 18. IF ANSWER TO QUESTION 15 IS “3” or “5”, GO TO QUESTION 18.]

16. Where/How do you park your car?

1. On the street
2. At company/college grounds
3. Public parking lot

[NOTE TO INTERVIEWER: NOW MOVE TO QUESTION 19.]

17. What is the approximate daily parking fee (in Lebanese Liras)?

1. Less than 3,000 LL
2. 3,000 LL – 4,999 LL
3. 5,000 LL – 6,999 LL
4. 7,000 LL – 9,999 LL
5. 10,000 LL or more

[NOTE TO INTERVIEWER: NOW MOVE TO QUESTION 19.]

18. What is the monthly subscription fee (in Lebanese Liras)?

1. Less than 50,000 LL
2. 50,000 LL – 99,000 LL
3. 100,000 LL – 149,000 LL
4. 150,000 LL – 199,000 LL
5. More than 200,000 LL

20. How many days per week do you commute to work/college?

1. 1
2. 2
3. 3
4. 4
5. 5
6. 6
7. 7

21. How flexible is your work/college arrangement when it comes to arrival time and departure time?

1. Completely flexible – [I arrive when I want to and leave when I want to.]
2. Partly flexible – [I can arrive a bit late but cannot leave before a certain time of day, or I have to arrive by a certain time but can leave a bit early.]

3. Not flexible – [I have to be on time in the morning and cannot leave before a certain time of day.]

Section 4: Scenarios

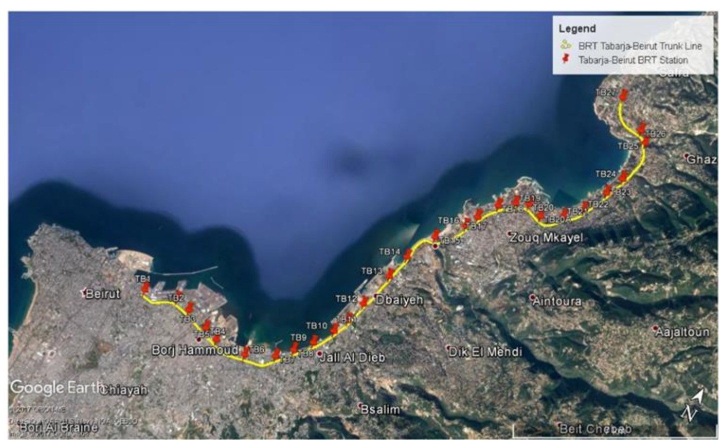
The Lebanese government is planning to develop a Bus Rapid Transit (BRT) line running from Tabarja towards the northern entrance of Beirut at Charles Helou station and already secured funding for the project through the World Bank.

In this section, you will be presented with different hypothetical scenarios for your work/college trip and asked to choose your preferred alternative. First, a brief explanation about the Bus Rapid Transit system will be provided.

Bus Rapid Transit (BRT)

The BRT is a bus system designed to increase the capacity and improve the reliability (consistent travel time for different days and seasons) of traveling by bus. It has the following main characteristics:

- **One dedicated lane per direction alongside the coastal highway with modern buses operating exclusively on these lanes.**
- **Stations located all along the highway at frequent intervals of around 1 km with passengers boarding/alighting only at these stations.**
- **Tickets are sold online and at stations with various options available (ticket for one trip, 5 trips, 10 trips, daily pass, …).**
- **BRT buses follow exact schedules, with 2 to 3minutes between two consecutive buses (the arrival time will be specified on screens at the station).**

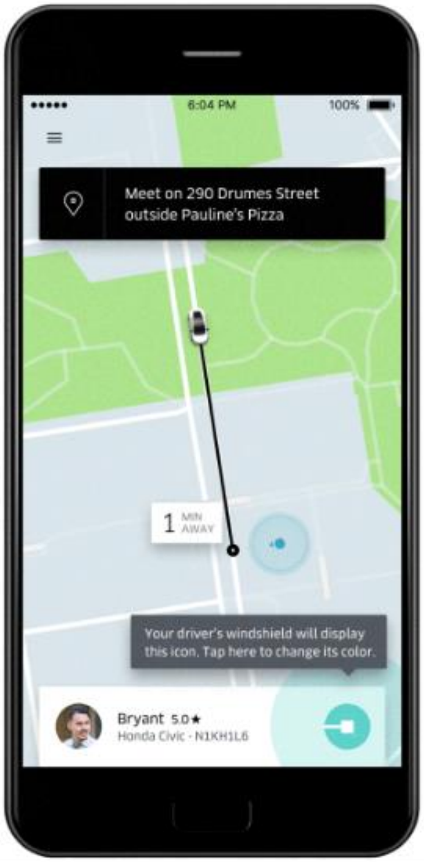


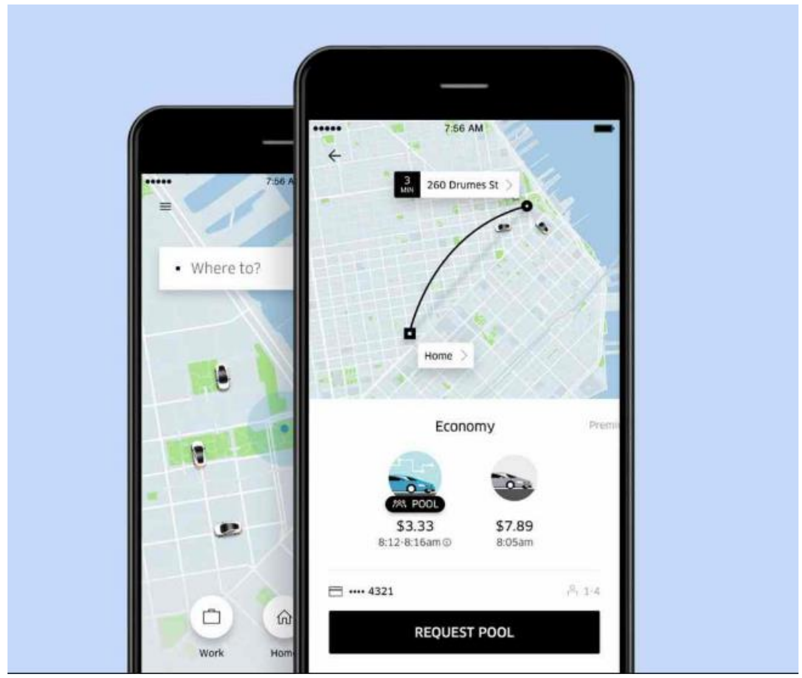
Below, you will be shown your current commute mode alongside several BRT options to determine whether you will switch to the BRT service. If you choose to use the BRT, you will be asked to choose how you will reach the nearest BRT station (access mode) and how you will commute from the final station to your work place/college (egress mode).

The access modes include:

- **Park & Ride:** you will drive to a parking near the BRT station where you leave your car and transfer to the BRT.
- **Service:** you will take a service from the nearest pick-up point to your residence to the nearest BRT station.
- **Bus:** you will take a bus from the nearest pick-up point to your residence to the nearest BRT station.
- **Taxi:** you will request a taxi from your home to the nearest BRT station.
- **Walking:** you will walk all the way from your residence to the BRT station.
- **Uber/Careem (private):** you will request a ride through "Uber" or "Careem" apps to travel from your residence to the BRT station. This is a private ride with no other passengers on board. The service has the following characteristics:
  - You can request a ride through the mobile app/website and will be instantaneously matched to the nearest driver available based on real time GPS data.
  - You can monitor the driver's location on the map alongside the estimated arrival time of the requested vehicle.
  - You can check driver's reviews submitted by other commuters.
  - The fare is automatically defined before requesting the ride with payment allowed through credit cards (with no direct cash transfer), or in cash.
  - You will be picked up from your residence.
- **Uber/Careem (shared):** Similar to the previous travel mode but the ride in this case will be shared with other passengers along the way and the fare will be split accordingly.

The egress modes available to leave the last BRT station are the same as the access modes presented. Only park & ride is not included since you will not have access to your car at that stage of the trip.





Now, you will be provided with 3 different scenarios for your commute to work/college, including the car option and the BRT option. In each scenario, a combination of access/egress modes to/from the BRT will be presented and not all options will be necessarily included. For each option, you will be presented with its travel time and cost components (such as time in the vehicle, waiting time, parking time, walking time, etc.). Please consider each scenario separately and indicate your preferred option based on how you would actually choose if faced by such scenario in reality.

THE BRT STUDIES IN LEBANON HAVE PROGRESSED IN THE DIRECTION OF ITS IMPLEMENTATION AND THE WORLD BANK WILL FUND MOST OF THE PROJECT. THE BRT WILL BE FULLY OPERATIONAL IN THE NEXT 5-6 YEARS. BY THEN, TRAVEL CHARACTERISTICS AND POLICIES MAY CHANGE SIGNIFICANTLY AND THE CURRENT TRAVEL TIMES AND COSTS MAY NO LONGER APPLY.

ACCORDINGLY, PLEASE BASE YOUR DECISION ON THE PROPOSED VALUES FOR EACH VARIABLE. THE SCENARIOS MIGHT NOT REFLECT YOUR CURRENT

TRAVEL CHARACTERISTICS. PLEASE <u>DO NOT</u> CONSIDER YOUR CURRENT TRAVEL TIME AND COSTS.

Scenario 1

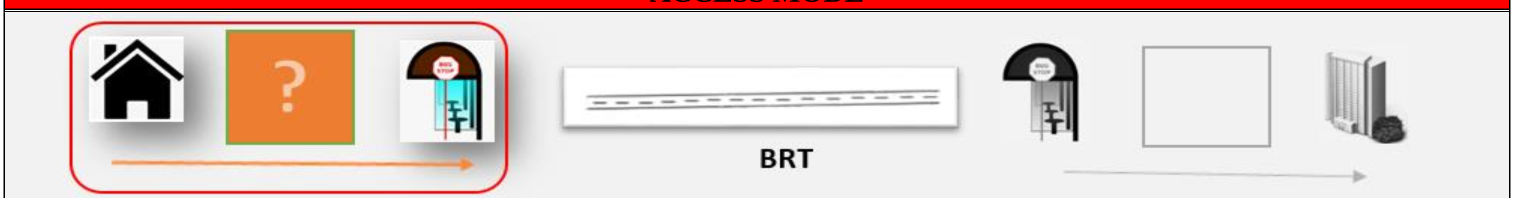
22. Imagine you are about to make a trip to work/college on a typical work day between 7 AM and 9 AM. Weather is sunny with a temperature of around 20ºC. You are carrying your typical gear and need to reach your work/college on time.

The mode choice process consists of 3 different steps:

<u>Step 1:</u> The Preferred BRT Trip

In this step, the BRT is imposed as main transport mode. You are asked to make two choices independently for the overall BRT trip: a choice of the preferred access mode adopted to commute from home to the BRT station, and then a choice of the preferred egress mode for commuting from the BRT station at which you will alight to your final destination.

ACCESS MODE



Access Modes Available

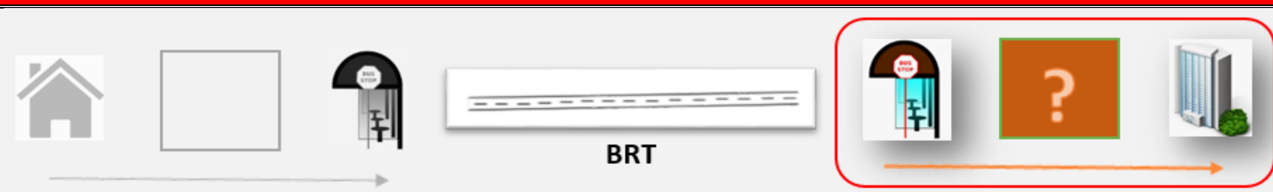
							UBER	uberPOOL
		1. Park & Ride	**2. Walk**	**3.Bus**	**4.Taxi**	**5.Service**	**6. Ridesourcing (private)**	**7. Ridesourcing (shared)**
	**In-Vehicle Travel Time (min)**	5	-	7	5	5	5	6
	**Walking Time (min)**	2	24	10	-	10	-	-

	Waiting Time (min)	2	-	5	10	3	3	3
	Fuel Cost (LL)	500	-	-	-	-	-	-
	Daily Parking Cost (LL)	3000	-	-	-	-	-	-
	Fare (LL)	-	-	1000	7000	2000	5000	3000
Selection								

MAIN TRANSPORT: BRT

	In-Vehicle Travel Time (min)	30
	Waiting Time (min)	2
	Fare (LL)	3000

EGRESS MODE



Available Egress Modes

		2. Walk	3.Bus	4.Taxi	5.Service	6. Ridesourcing (private)	7. Ridesourcing (shared)

	In-Vehicle Travel Time (min)	-	7	5	5	5	6
	Walking Time (min)	24	10	-	10	-	-
	Waiting Time (min)	-	5	10	3	3	3
	Fare (LL)	-	1000	7000	2000	5000	3000
Selection							

<u>Step 2:</u> Choice Confirmation

In this step, you will be asked to confirm the choices you made in step 1. You will be presented with the characteristics of the overall BRT trip selected in the previous step and will be asked to confirm your selection. You can choose to go back to step 1 to vary your selection or you can confirm your current selection. If you confirm your choice, you will no longer be able to go back to step 1.

BRT Trip Selected		
	In-Vehicle Travel Time (min)	**Sum for access, BRT, and egress**
	Average Walking Time (min)	**Sum for access and egress**
	Average Waiting Time (min)	**Sum for access, BRT, and egress**
	Fuel Cost (LL)	**Only if Access is “Park & Ride”, 0 otherwise**
	Daily Parking Cost (LL)	**Only if Access is “Park & Ride”, 0 otherwise**
	Fare (LL)	**Sum for access, BRT, and egress**
Confirm Your Selection		

Go Back to Step 1

<u>Step 3:</u> Choice between Preferred BRT trip and Commute by Private Car

In this step, you will have to choose between your preferred BRT trip selected in the previous steps and commuting by private car from origin to destination.

Overall Trip			
		BRT Trip Selected	**Private Car**
	In-Vehicle Travel Time (min)	**Sum for access, BRT, and egress**	**59**
	Walking Time (min)	**Sum for access and egress**	**4**
	Waiting Time (min)	**Sum for access, BRT, and egress**	**0**
	Fuel Cost (LL)	**Only if Access is "Park & Ride", 0 otherwise**	**4000**
	Daily Parking Cost (LL)	**Only if Access is "Park & Ride", 0 otherwise**	**5000**
	Fare (LL)	**Sum for access, BRT, and egress**	
Selection			

Scenario 2

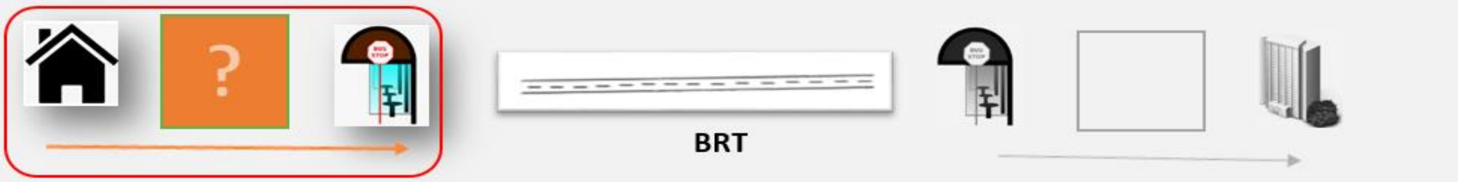
23. Imagine you are about to make a trip to work/college on a typical work day between 7 AM and 9 AM. Weather is sunny with a temperature of around 20ºC. You are carrying your typical gear and need to reach your work/college on time.

The mode choice process consists of 3 different steps:

<u>Step 1:</u> The Preferred BRT Trip

In this step, the BRT is imposed as main transport mode. You are asked to make two choices independently for the overall BRT trip: a choice of the preferred access mode adopted to commute from home to the BRT station, and then a choice of the preferred egress mode for commuting from the BRT station at which you will alight to your final destination.

ACCESS MODE



Access Modes Available

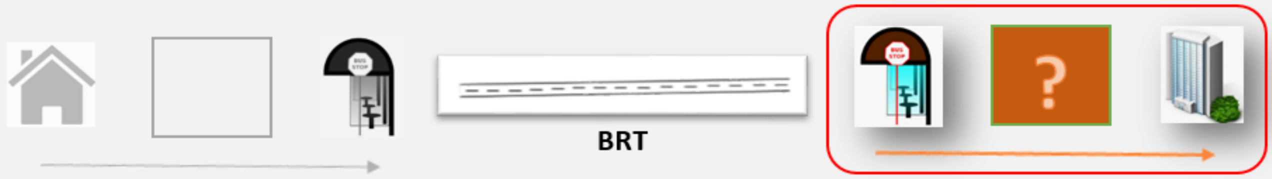
		1. Park & Ride	2. Walk	3.Bus	4.Taxi	5.Service	6. Ridesourcing (private)	7. Ridesourcing (shared)
	In-Vehicle Travel Time (min)	5	-	7	5	5	5	6
	Walking Time (min)	2	24	10	-	10	-	-
	Waiting Time (min)	2	-	5	10	3	3	3
	Fuel Cost (LL)	500	-	-	-	-	-	-
	Daily Parking Cost (LL)	3000	-	-	-	-	-	-
	Fare (LL)	-	-	1000	7000	2000	5000	3000

Selection

MAIN TRANSPORT: BRT

	In-Vehicle Travel Time (min)	30
	Waiting Time (min)	2
	Fare (LL)	3000

EGRESS MODE



Available Egress Modes

		2. Walk	3.Bus	4.Taxi	5.Service	6. Ridesourcing (private)	7. Ridesourcing (shared)
	In-Vehicle Travel Time (min)	-	7	5	5	5	6
	Walking Time (min)	24	10	-	10	-	-
	Waiting Time (min)	-	5	10	3	3	3
	Fare (LL)	-	1000	7000	2000	5000	3000
Selection							

<u>Step 2:</u> Choice Confirmation

In this step, you will be asked to confirm the choices you made in step 1. You will be presented with the characteristics of the overall BRT trip selected in the previous step and will be asked to confirm your selection. You can choose to go back to step 1 to vary your selection or you can confirm your current selection. If you confirm your choice, you will no longer be able to go back to step 1.

(Selected Access Mode) + BRT + (Selected Egress Mode)		
	In-Vehicle Travel Time (min)	**Sum for access, BRT, and egress**
	Average Walking Time (min)	**Sum for access and egress**
	Average Waiting Time (min)	**Sum for access, BRT, and egress**
	Fuel Cost (LL)	**Only if Access is "Park & Ride", 0 otherwise**
	Daily Parking Cost (LL)	**Only if Access is "Park & Ride", 0 otherwise**
	Fare (LL)	**Sum for access, BRT, and egress**
Confirm Your Selection		
Go Back to Step 1		

<u>Step 3:</u> Choice between Preferred BRT trip and Commute by Private Car

In this step, you will have to choose between your preferred BRT trip selected in the previous steps and commuting by private car from origin to destination.

Overall Trip			
		(Selected Access Mode) + BRT + (Selected Egress Mode)	**Private Car**
	In-Vehicle Travel Time (min)	**Sum for access, BRT, and egress**	**59**
	Walking Time (min)	**Sum for access and egress**	**4**

	**Waiting Time (min)**	**Sum for access, BRT, and egress**	**0**
	**Fuel Cost (LL)**	**Only if Access is “Park & Ride”, 0 otherwise**	**4000**
	**Daily Parking Cost (LL)**	**Only if Access is “Park & Ride”, 0 otherwise**	**5000**
	**Fare (LL)**	**Sum for access, BRT, and egress**	
Selection			

Scenario 3

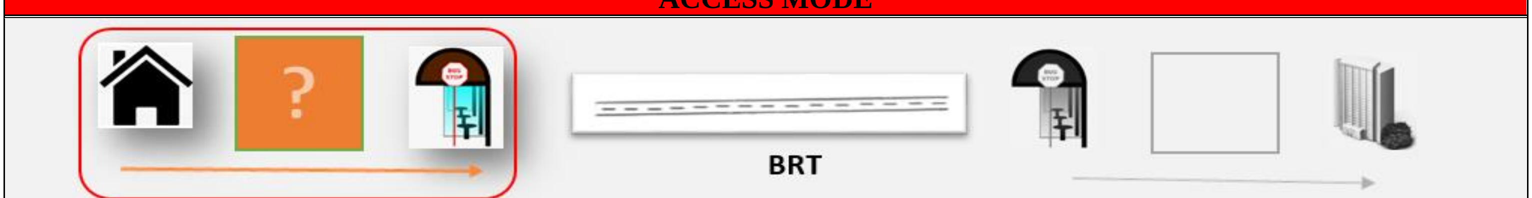
24. Imagine you are about to make a trip to work/college on a typical work day between 7 AM and 9 AM. Weather is sunny with a temperature of around 20ºC. You are carrying your typical gear and need to reach your work/college on time.

The mode choice process consists of 3 different steps:

<u>Step 1:</u> The Preferred BRT Trip

In this step, the BRT is imposed as main transport mode. You are asked to make two choices independently for the overall BRT trip: a choice of the preferred access mode adopted to commute from home to the BRT station, and then a choice of the preferred egress mode for commuting from the BRT station at which you will alight to your final destination.

ACCESS MODE



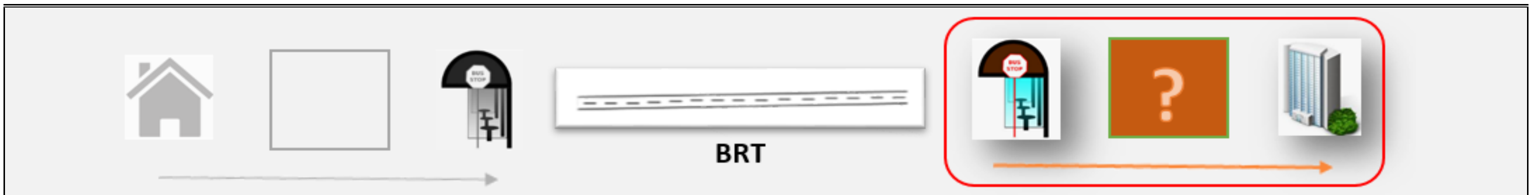
Access Modes Available

		1. Park & Ride	2. Walk	3.Bus	4.Taxi	5.Service	6. Ridesourcing (private)	7. Ridesourcing (shared)
	In-Vehicle Travel Time (min)	5	-	7	5	5	5	6
	Walking Time (min)	2	24	10	-	10	-	-
	Waiting Time (min)	2	-	5	10	3	3	3
	Fuel Cost (LL)	500	-	-	-	-	-	-
	Daily Parking Cost (LL)	3000	-	-	-	-	-	-
	Fare (LL)	-	-	1000	7000	2000	5000	3000
Selection								

MAIN TRANSPORT: BRT

	In-Vehicle Travel Time (min)	30
	Waiting Time (min)	2
	Fare (LL)	3000

EGRESS MODE



Available Egress Modes							
						UBER	uberPOOL
		2. Walk	3.Bus	4.Taxi	5.Service	6. Ridesourcing (private)	7. Ridesourcing (shared)
	In-Vehicle Travel Time (min)	-	7	5	5	5	6
	Walking Time (min)	24	10	-	10	-	-
	Waiting Time (min)	-	5	10	3	3	3
	Fare (LL)	-	1000	7000	2000	5000	3000
Selection							

Step 2: Choice Confirmation

In this step, you will be asked to confirm the choices you made in step 1. You will be presented with the characteristics of the overall BRT trip selected in the previous step and will be asked to confirm your selection. You can choose to go back to step 1 to vary your selection or you can confirm your current selection. If you confirm your choice, you will no longer be able to go back to step 1.

(Selected Access Mode) + BRT + (Selected Egress Mode)		
	In-Vehicle Travel Time (min)	Sum for access, BRT, and egress

	Average Walking Time (min)	**Sum for access and egress**
	Average Waiting Time (min)	**Sum for access, BRT, and egress**
	Fuel Cost (LL)	**Only if Access is “Park & Ride”, 0 otherwise**
	Daily Parking Cost (LL)	**Only if Access is “Park & Ride”, 0 otherwise**
	Fare (LL)	**Sum for access, BRT, and egress**
Confirm Your Selection		
Go Back to Step 1		

<u>Step 3:</u> Choice between Preferred BRT trip and Commute by Private Car

In this step, you will have to choose between your preferred BRT trip selected in the previous steps and commuting by private car from origin to destination.

Overall Trip			
		(Selected Access Mode) + BRT + (Selected Egress Mode)	**Private Car**
	In-Vehicle Travel Time (min)	**Sum for access, BRT, and egress**	**59**
	Walking Time (min)	**Sum for access and egress**	**4**
	Waiting Time (min)	**Sum for access, BRT, and egress**	**0**
	Fuel Cost (LL)	**Only if Access is “Park & Ride”, 0 otherwise**	**4000**

	Daily Parking Cost (LL)	**Only if Access is "Park & Ride", 0 otherwise**	**5000**
	Fare (LL)	**Sum for access, BRT, and egress**	
Selection			

Section 5: Attitude towards Different Travel Modes

Now we will ask you about your attitude and perception towards different travel modes. In case you do not use a particular mode, please answer the related questions based on your perception of the travel mode in question and what you have heard of it.

25. Please indicate your level of agreement with the following statements about using and owning cars in Lebanon.

	Strongly disagree	Disagree	Neither satisfied nor dissatisfied	Agree	Strongly agree
a. I like using the car as a mode of commuting	1	2	3	4	5
b. I can count on the car to get me to work/college on time					
c. The car offers me the flexibility I need for my schedule	1	2	3	4	5
d. Using the car does not cost much	1	2	3	4	5
e. Owning a car brings prestige	1	2	3	4	5

26. Please indicate your level of agreement with the following statements about buses in Lebanon. In case you do not use the bus, please answer the questions based on your perception of this travel mode and what you have heard of it.

	Strongly disagree	Disagree	Neither satisfied nor dissatisfied	Agree	Strongly agree

a. I like using the bus as a mode of commuting	1	2	3	4	5
b. I can count on the bus to get me to work/college on time	1	2	3	4	5
c. The bus offers me the flexibility I need for my schedule	1	2	3	4	5
d. Buses have poor hygiene	1	2	3	4	5
e. I feel safe in the bus	1	2	3	4	5

27. **Please indicate your level of agreement with the following statements concerning improved bus services in Lebanon such as the proposed BRT:**

	Strongly disagree	**Disagree**	**Neither satisfied nor dissatisfied**	**Agree**	**Strongly agree**
a. I am willing to use the BRT if it reduces my commute time substantially.	1	2	3	4	5
b. I am willing to use the BRT if the fare is much cheaper than the cost of using my car.	1	2	3	4	5
c. I wouldn't mind being around other people when using the BRT.	1	2	3	4	5
d. I wouldn't mind walking few minutes to get to or from a BRT station.	1	2	3	4	5

28. **Have you ever used Uber/Careem or similar services inside or outside Lebanon?**
    8. Yes
    9. No

29. **Based on your personal experience or anything you have seen, read, or heard, please indicate your level of agreement with the following statements concerning Uber/Careem and similar services:**

	Strongly disagree	**Disagree**	**Neither satisfied nor dissatisfied**	**Agree**	**Strongly agree**
a. I like the idea of using Uber/Careem as a mode of commuting	1	2	3	4	5

b. Knowing the waiting time for pick-up is an attractive feature	1	2	3	4	5
c. The driver review system enhances Uber/Careem's safety and overall service	1	2	3	4	5
d. The ability to track the driver's live location is an attractive feature	1	2	3	4	5

Section 6: Socio-Economic and Demographic Questions

In this section, we will ask you a few questions about characteristics of your household and household members to ensure that the Lebanese population is well represented in the sample. Please do not include anyone visiting for a short stay nor live-in domestic workers. If you live with roommates/housemates, please report characteristics of your family household.

30. What is your gender?

1. Male
2. Female

31. In which of the following categories does your age fall?

1. 18-24
2. 25-29
3. 30-39
4. 40-49
5. 50-64
6. 64+
7. I prefer not to answer

[NOTE TO INTERVIEWER: IF ANSWER TO QUESTION 1 IS "a" or "b", GO TO QUESTION 32; OTHERWISE, GO DIRECTLY TO QUESTION 33]

32. What is the highest educational level that you completed?

1. No formal education
2. Less than secondary/high school diploma
3. Secondary/high school diploma (12 years of schooling)
4. Technical or vocational school
5. Some college/university
6. University undergraduate/bachelor degree or equivalent
7. Postgraduate, master's degree, doctorate
8. Other, please specify:………………………………..

33. With whom do your share your current residence?

1. I live alone
2. With a partner, without children
3. With a partner, with children
4. Alone with children
5. Roommates/flat mates
6. I live with my parents at their house
7. Other (please specify): ……………………………………………….

34. **How many persons, including yourself but not domestic helper(s), live in your household?**
    1. 1
    2. 2
    3. 3
    4. 4
    5. 5
    6. 6
    7. 7
    8. 8+

35. **How many people in your household (including you) have a driver's license?**
    1. 0
    2. 1
    3. 2
    4. 3
    5. 4
    6. 5
    7. 6
    8. 7
    9. 8+

36. **What is your family <u>monthly</u> income range (approximately) in <u>Lebanese Liras</u>?**
    1. 0 – 1,499,999 LL
    2. 1,500,000 LL - 2,999,999 LL
    3. 3,000,000 LL – 4,499,999 LL
    4. 4,500,000 LL - 5,999,999 LL
    5. 6,000,000 LL – 7,499,999 LL
    6. 7,500,000 LL - 9,999,999 LL
    7. 10,000,000 LL – 14,999,999 LL
    8. 15,000,000 LL – 19,999,999 LL
    9. 20,000,000 LL – 29,999,999 LL
    10. 30,000,000 LL or more
    11. Refuse to answer
    12. Don't know

37. **What is your personal <u>monthly</u> income range (approximately) in <u>Lebanese Liras</u>?**
    1. 0 – 1,499,999 LL
    2. 1,500,000 LL - 2,999,999 LL
    3. 3,000,000 LL – 4,499,999 LL
    4. 4,500,000 LL - 5,999,999 LL

5. 6,000,000 LL – 7,499,999 LL
6. 7,500,000 LL - 9,999,999 LL
7. 10,000,000 LL – 14,999,999 LL
8. 15,000,000 LL or more
9. Refuse to answer
10. Don't know

THANK YOU FOR PARTICIPATING IN THIS SURVEY. IF YOU HAVE ANY COMMENT OR CONCERN ABOUT THE SURVEY, FEEL FREE TO SHARE IT WITH US:

Please add your comments, if any, here:

APPENDIX B: BASE VALUES DEFINITION FOR FORECASTING

This appendix provides a description of the definition of base values used for forecasting. Base values for trips originating in Tabarja (Zone 2) and destined to Achrafieh (Zone A) will be defined to illustrate the adopted approach for the definition of the values. Base values for other origin-destination couples were defined following the same approach but their values will not be discussed in detail in this appendix.

For travel time, in-vehicle travel time was defined for all main travel, access, and egress modes. Walking and waiting times were also defined separately by mode when applicable. Car IVTT was defined based on Google Maps estimates during the AM peak hour. As for the BRT, an average speed of 30 km was assumed for the BRT which is similar to the speed of Istanbul's BRT and other similar systems. The road distance along the coastal highway where the BRT is to be developed was obtained from Google Maps and the average speed was used to compute the trip duration which turned out to be 49 min for a trip from Tabarja to Achrafieh. For feeders, the travel time were also obtained from Google Maps from the centroid of the zone to the expected location of the nearest BRT station. A base value of 5 min was thus adopted for park and ride. 20% and 30% increases were applied for jitney and bus respectively due to their frequent stops and lower operating speeds. A 10% decrease in IVTT was adopted for private ridesourcing as it provides an un-interrupted trip while avoiding parking time when compared to park and ride. Shared ridesourcing was assigned a 20% increase in IVTT compared to the private form of the service due to pick-ups of other passengers, though that will translate into faster times than jitneys as the mobile platform incorporates optimal routing and matching algorithms while jitney pick-up are more random and less planned. For feeders, IVTT values were not rounded due to their low magnitude and minor variation across each other. The base values for all IVTTs for trips between zones 2 and A are summarized in the Table B.1:

Table B.1: Base Values for In-Vehicle Travel Time

IVTT (Car)	88 min	IVTT (Shared Ridesourcing, Access)	5.4 min
IVTT (BRT)	49 min	IVTT (Bus, Egress)	12 min
IVTT (Park and Ride, Access)	5 min	IVTT (Jitney, Egress)	11 min
IVTT (Bus, Access)	6.5 min	IVTT (Private Ridesourcing, Egress)	9 min
IVTT (Jitney, Access)	6 min	IVTT (Shared Ridesourcing, Egress)	11 min
IVTT (Private Ridesourcing, Access)	4.5 min		

Walking time was not included for the BRT due to the absence of transfers as the BRT operated on one line. The walking time to cross pedestrian bridges and reach the BRT stop were assigned to the feeders. Car walking time was inflated for zones where parking is limited as commuters might be forced to park a little farther than their final destination. Among feeders, ridesourcing had the lowest walking time as commuters are picked-up from home and dropped-off right at the station. For park and ride, there is need to walk from the parking to the station, while bus and jitney passengers have to walk to their stations. For egress, lower walking time were used for bus and jitney as their stations are less spaced and more numerous inside the capital. When walking is adopted for access or egress, base values were defined using Google Maps. The base values for all walking times for trips between zones 2 and A are summarized in the following Table B.2:

Table B.2: Base Values for Walking Time

Walking Time (Car)	5 min	Walking Time (Shared Ridesourcing, Access)	1 min
Walking Time (Walk, Access)	10 min	Walking Time (Walk, Egress)	15 min
Walking Time (Park and Ride, Access)	2 min	Walking Time (Bus, Egress)	2 min
Walking Time (Bus, Access)	3 min	Walking Time (Jitney, Egress)	2 min
Walking Time (Jitney, Access)	3 min	Walking Time (Private Ridesourcing, Egress)	1 min
Walking Time (Private Ridesourcing, Access)	1 min	Walking Time (Shared Ridesourcing, Egress)	1 min

Waiting time do not apply for car or when walking is adopted as feeder. For the BRT, a headway of 4 minutes as the BRT study performed by Khatib & Alami and TMS Consult mentions an expected headway between 2 and 5 minutes. This translates to an average waiting time of 2 min which was adopted as base value. A higher headway was adopted for buses due to lower demand on feeder lines. A 10 minutes headway was assumed for buses at the access stage which translates into a waiting time of 5 minutes on average, with lower values adopted for egress as operations are denser in the capital. For jitney, a lower waiting time of 4 minutes was assumed for access as vehicles pass more frequently than buses due to their lower capacity and higher number. Lower waiting times were adopted for ridesourcing as the service allows requesting a ride before getting ready and tracking the vehicle, which reduces the net waiting time. The base values for all waiting times for trips between zones 2 and A are summarized in Table B.3:

Table B.3: Base Values for Waiting Time

Waiting Time (BRT)	2 min	Waiting Time (Bus, Egress)	3 min
Waiting Time (Bus, Access)	5 min	Waiting Time (Jitney, Egress)	2 min
Waiting Time (Jitney, Access)	4 min	Waiting Time (Private Ridesourcing, Egress)	2 min
Waiting Time (Private Ridesourcing, Access)	2 min	Waiting Time (Shared Ridesourcing, Egress)	2 min
Waiting Time (Shared Ridesourcing, Access)	2 min		

As for travel costs, base values were also defined separately for each mode. For cars, the fuel cost was computed based on distance and an average fuel consumption of 150 km per tank. Daily parking costs were assumed to be 7,000 L.L. in Municipal Beirut, and 3,000 L.L. or 5,000 L.L. outside it depending on the availability of free parking in the zone of interest. For the BRT the fares were computed similarly to the approach from Khatib & Alami and TMS Consult who used a dynamic rate that equals 1000 + 120*distance (L.L.). This translates to 3,880 L.L. for the 24 km trip from Tabarja to Achrafieh, and a rounded base value of 4,000 L.L. was used as such. BRT fares were rounded to the closest 1,000

L.L. For park and ride, a daily fare of 5,000 L.L. was assumed. Bus and jitney fares were set at 1,000 L.L. and 2,000 L.L. which are the current prices in the market and the same rates were used in the study from Khatib & Alami and TMS Consult. When the access/egress trips exceed 3 km, the rates were raised to 1,500 L.L. for buses and 4,000 L.L. for jitney. As for ridesourcing, Careem's fare estimator was used and its minimum fare of 5,000 L.L. was adopted for private ridesourcing over short trips in zones adjacent to the BRT, while higher fares resulted for long trips. As for shared ridesourcing, a 40% decrease was applied compared to the private form of the service as Uber estimates a reduction of one third on average compared to the private fare while the company recently launched the enhanced Uber Express Pool which features enhanced routing and matching algorithms and allows for further fare reductions, thus a 40% decrease was adopted. The base values for all costs for trips between zones 2 and A are summarized in Table B.4:

Table B. 4: Base Values for Trip Costs

Fuel Cost (Car)	5,420 L.L.	Fare (Private Ridesourcing, Access)	5,000 L.L.
Daily Parking Cost (Car)	7,000 L.L.	Fare (Shared Ridesourcing, Access)	3,000 L.L.
Fare (BRT)	4,000 L.L.	Fare (Bus, Egress)	1,000 L.L.
Daily Parking Cost (Park and Ride, Access)	5,000 L.L.	Fare (Jitney, Egress)	2,000 L.L.
Fare (Bus, Access)	1,000 L.L.	Fare (Private Ridesourcing, Egress)	5,000 L.L.
Fare (Jitney, Access)	2,000 L.L.	Fare (Shared Ridesourcing, Egress)	3,000 L.L.