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Modeling demand for ridesourcing as feeder for high capacity mass transit systems with an application to the planned Beirut BRT

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ABSTRACT

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.

1. Introduction

Ridesourcing, also known as ride-hailing or transportation network companies (TNCs), is emerging as a main travel mode in dense urban areas. Ridesourcing provides commuters with point-to-point rides through smartphone requests and incorporates tracking options, enhanced payment methods, and a review-based selection of drivers, with an aim to elevate the travel experience of its users (Rayle et al., 2016). After passing regulation in California and hitting streets in 2012 (Cohen and Shaheen, 2018), the service was quickly established in the transportation industry with diverse platforms (such as Uber, Lyft, Careem, and DiDi) reaching wide

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coverage over multiple 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% of intra-city trips and is 12 times larger than the market share of taxi trips. The 570,000 vehicle miles of travel (VMT) commuted daily by ridesourcing represent 20% of intra-San Francisco VMT (SFCTA, 2017). Growth trends reveal no slowing down with ridesourcing trips predicted to outnumber bus commutes in the United States by the end of 2018 and become the largest low capacity public transportation mode (Schaller, 2018).

Ridesourcing is disrupting the travel industry and steadily gaining market share though its impact on other travel modes remains ambiguous. Consensus from previous studies suggests a negative impact on the taxi industry as ridesourcing allows flexible work schedules for drivers and more competitive pricing schemes for riders which enforces its position as an increasingly attractive substitute to traditional taxis (Contreras and Paz, 2018; Greenwood and Wattal, 2017; Hall and Krueger, 2018). This has caused regulatory challenges and raised calls for a reform in public policy to properly address the emerging service which led some cities to ban or enforce strong regulations on ridesourcing operations. For example, the city of Toronto passed a law in July 2016 to limit the number of ridesourcing vehicles and impose special licenses and criminal background checks for drivers (Toronto, 2016). As for the impact on transit, current findings are inconclusive. On the one hand, ridesourcing competes with transit for door-to-door travel as suggested by findings from a survey-based study in San Francisco which revealed that 24% of ridesourcing users would have used the bus if the service was not available (Rayle et al., 2014). On the other hand, ridesourcing can benefit transit by providing first-mile-last-mile connections and extending its catchment area (Shaheen et al., 2015). Ridesourcing can provide access for non-vehicle owners and serve small markets where taxi and buses are limited or unavailable (Cohen and Shaheen, 2018). As such, 29 partnerships have been 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). Data sharing is another motive for such partnerships as it allows better transit planning in the future (Curtis et al., 2019).

This research aims to investigate the potential of ridesourcing as feeder to high capacity mass transit systems and to answer questions on the complementarity between ridesourcing and public transportation. At a methodological level, we provide a demand modeling framework that incorporates all stages of a multi-modal trip simultaneously, which allows for a flexible modeling of the choice between uni-modal (e.g. car) or multi-modal (e.g. transit) 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 has been tested in limited settings so far. This study contributes further towards unveiling the impact of ridesourcing on transit particularly in its ability to improve first-mile-last-mile connections. Moreover, the framework is applied through a case study of the planned Beirut Bus Rapid Transit (BRT) which provides insights on the potential of ridesourcing in developing countries. The model is also used for policy analysis which provides planners and policy makers with strategies for an effective integration that does not negatively affect transit. The remainder of this paper is organized as follows. Section 2 reviews the literature on first-mile-last-mile connections and ridesourcing demand and its relation to transit. Section 3 formulates the model and the likelihood function. An application on the planned Beirut BRT is presented in Section 4. Section 5 discusses model estimation and results. The model is then used in Section 6 for policy analysis, before concluding the paper in Section 7.

2. Literature review

This section provides a review of the literature on the first-mile-last-mile problem, the factors affecting demand for ridesourcing, and its relation and integration with transit. The gaps in the literature on ridesourcing and its integration with transit are also discussed.

2.1. First-mile-last-mile connections to transit

The first-mile-last-mile problem is a major topic in transportation planning. Choice models have been developed for access or egress stages of high capacity transit systems. For example, 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 and should be grouped into nests to capture their similarities. 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.

Other studies include more than one selection in the stated preference (SP) survey design which provides 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.

Other studies have incorporated multiple stages of transit trips. Polydoropoulou and Ben-Akiva (2001) introduced a framework to model demand for different modes in a multi-modal trip. They designed a computer-based SP survey that included 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 concludes 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 Molin (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 distinguished 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 for 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 selection of access, egress, and main travel modes.

The potential of new mobility concepts as feeders for mass transit has also been explored as these are expected to disrupt the transportation industry. 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 was defined as the main travel mode with differentiation between 1st class and 2nd class travelers. The access mode was predefined 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.

2.2. Factors affecting demand for ridesourcing

Planning for ridesourcing relies primarily on identifying the main features affecting demand for the service. 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). A California-based study (Alemi et al., 2018a) 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. Analogous conclusions have been reached for Toronto (Young and Farber, 2019) and based on the United States' 2017 National Household Travel Survey (Grahn et al., 2019), with more eagerness for ridesourcing among the younger generation, and higher interest amid wealthier segments.

Residents of urban areas use ridesourcing more frequently as mixed land use, dense road networks, population, and employment are found to be major drivers for using the service (Clewlow et al., 2017; Grahn et al., 2019; Yu and Peng, 2019), reflecting that a relation exists between the built environment and demand for ridesourcing and that potential for the service is largest in big cities.

Ridesplitting (UberPool, Lyft Line, …) matches riders with compatible origins and destinations in real time to the same driver and vehicle, allowing them to split the fare and reduce the commute cost (Shaheen et al., 2016). This type of service allows ridesourcing to reach higher market share and to become more accessible to larger sectors of the community as customers can save 25% to 60% of the typical fare by sharing rides with other passengers (Shaheen and Cohen, 2019). Chen et al. (2017) studied ridesplitting in the Chinese city of Hangzhou through data from DiDi Hitch and concluded that ridesplitting induces larger waiting times but is nonetheless attractive for long distance trips as it allows to reduce the associated travel costs. Findings from North America also reflect high potential for pooled rides as passenger survey studies revealed that the average ridesourcing occupancy in San Francisco was 2.1 passengers per trip even before introducing pooled services (UberPOOL, Lyft Line, …). Moreover, ridesplitting constituted 20% of total ridesourcing trips in Massachusetts (Shaheen and Cohen, 2019).

Alemi et al. (2018b) built adoption models with latent constructs to capture heterogeneous preferences of commuters and found that highly educated and independent individuals are most likely to adopt ridesourcing and have a higher willingness to pay to reduce their travel time. Tarabay and Abou-Zeid (2019) investigated the potential of ridesourcing for social/recreational trips in the context of a private urban university in the city of Beirut through a choice model developed based on RP and SP data. The study forecasted that around 22% of students would switch from their current modes to ridesourcing if well implemented, with a 40% fare reduction driving the switching proportion beyond 30%.

2.3. Complementarity between ridesourcing and transit

Consensus on the actual impacts of ridesourcing on public transportation is not yet fully formed, but the topic has been a subject of interest recently (see, for example, a review in Tirachini, 2019)). The impact of ridesourcing on transit is too small to induce any clear complementary or substitutive relation, but with the service growing exponentially, it is expected to have an important effect on the ridership levels of all other modes in the future, including transit (Habib, 2019; Young and Farber, 2019). Hence, it is essential to investigate further the relation of ridesourcing to transit and unfold the role of ridesourcing at the first-mile-last-mile stage.

Strong claims have been made about ridesourcing acting as a substitute to transit. Graehler et al. (2018) estimated that ridesourcing services compete with transit and induce a yearly decrease of 1.7% and 1.3% in heavy rail and bus ridership, respectively, in the United States. On the other hand, opposing claims have been made arguing for the complementarity between ridesourcing and transit. Contreras and Paz (2018) suggested a complementary effect between ridesourcing and transit ridership in Las Vegas based on a linear regression analysis built on a time-series travel dataset. 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). Yan et al. (2019) tested this partnership by developing a demand model for an integrated transit system at the University of Michigan Ann Arbor through combined RP and SP 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 transit on underutilized lines thus decreasing operating costs. 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.

2.4. Gaps in the literature

Demand modeling for ridesourcing as feeder to transit has not yet been tackled in the literature, to the authors' knowledge, in the context of suburban areas where the challenge of first-mile-last-mile connectivity mainly lies. In addition, ridesourcing characteristics have rarely been investigated in developing countries where ridership patterns may not mirror the observed trends in developed urban cities. Studies should be performed in different settings before reaching global understanding of the impacts of the new technology. This research aims to address these gaps.

3. Model formulation

The problem addressed in this paper involves selecting between uni-modal trips (mainly car 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 (Train, 2009).

3.1. The choice model

The choice model is based on the random utility maximization theory (Ben-Akiva and Lerman, 1985). The utilities of all travel mode combinations are specified 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. Let J be the set of all alternatives with $j \in J$ the index of any particular one, where an alternative is a mode or combination of modes needed to conduct the entire trip. The utility of alternative j is expressed 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:

$$V_{j,n,t} = \sum_{m=1}^{M} I_m^{Main,j} V_{m,n,t}^{Main} + \sum_{a=1}^{A} I_a^{Acc,j} V_{a,n,t}^{Acc} + \sum_{e=1}^{E} I_e^{Egr,j} V_{e,n,t}^{Egr} \tag{2}$$

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:

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

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

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

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. Each of $\sum_{a=1}^{A} I_a^{Acc,j}$ and $\sum_{e=1}^{E} I_e^{Egr,j}$ can be either 0 for uni-modal trips, or 1 for multi-modal trips assuming that only one access and one egress mode 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 (mainly 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^f), 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 (as in Ben-Akiva and Abou-Zeid, 2013).

$\omega_{j,n}$ is a random time-invariant component that is specific to alternative j and indivdiual 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 a disturbance term having 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.

3.2. 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 choices 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:

$$y_{j,n,t} = \begin{cases} 1 \; if \quad alternative \;\; j \;\; is \;\; selected \;\; by \;\; individual \;\; n \;\; in \;\; scenario \;\; t \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{10}$$

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

$$P(Y_n| \, X_n, \beta^f, \vec{\lambda})= \int_{\omega_M^{Main}} \cdots \int_{\omega_1^{Main}} \int_{\omega_A^{Acc}} \cdots \int_{\omega_1^{Acc}} \int_{\omega_E^{Egr}} \cdots \int_{\omega_1^{Egr}} \int_{\beta_{K_r}^r} \cdots \int_{\beta_1^r} \left[\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{e^{V_{j,n,t}+\omega_{j,n}}}{\sum_{p=1}^{J} e^{V_{p,n,t}+\omega_{p,n}}}\right)^{y_{j,n,t}}\right] \prod_{m=1}^{M} f(\omega_{m,n}^{Main}) \prod_{a=1}^{A} f(\omega_{a,n}^{Acc}) \prod_{e=1}^{E} f(\omega_{e,n}^{Egr}) \prod_{k=1}^{K_r} f(\beta_{k,n}^r) \, d\omega_1^{Main} \cdots d\omega_M^{Main} d\omega_1^{Acc} \cdots d\omega_A^{Acc} d\omega_1^{Egr} \cdots d\omega_E^{Egr} d\beta_1^r \cdots d\beta_{K_r}^r \tag{11}$$

Where $f(.)$ is the probability density function of the corresponding random term, and the error components are assumed to be uncorrelated across modes. $\vec{\lambda}$ 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:

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

Where N is the sample size. The log-likelihood becomes the following:

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

4. Application

In this section, the proposed modeling framework is applied in the context of a case study of the planned Beirut Bus Rapid Transit (BRT) in Lebanon. This application gives a better overview on the potential of integrating ridesourcing with transit. The study focuses only on trips entering Beirut during the morning peak through its northern entrance in accordance with the planned BRT coverage, and is limited to current car users as these account for the majority of motorized trips circulating in the Greater Beirut Area (GBA). This approach reduces the number of alternatives in the model as only two main modes will be considered: car and BRT. An overview of the transportation context in Lebanon is provided followed by a discussion of the study area and the experimental design including survey design, data collection, and descriptive analysis.

4.1. Transportation context in Lebanon and the planned Beirut BRT

Lebanon suffers from a growing traffic congestion problem, especially in its capital city Beirut and its suburbs, leading to 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 dependence and concentration of jobs and services in the capital. High capacity transit systems that operate on fixed alignments with their own right of way are absent, and cars keep dominating despite low fares of jitneys (shared taxis) and buses due to reliability concerns and bad perception by the public (Danaf et al., 2014). Car dependence is reflected by high car ownership of 1 car per 3 persons, with an average occupancy of 1.2 persons per vehicle (MoE/UNDF/GEF, 2015). The private car is responsible for over 80% of motorized trips conducted in the GBA during the AM peak, a share that is larger outside GBA where public transportation is even more deficient (IBI/TEAM, 2009).

The World Bank and local authorities are moving towards developing a BRT system along the northern entrance to Beirut to mitigate the daily congestion and its social and environmental impacts. The proposed system will run along a 24-km stretch of the northern coastal highway from Tabarja in the North towards Beirut. Twenty-eight stations will be located along the corridor at 850-m intervals and buses will operate at pre-defined headways and schedules (CDR/World Bank, 2017).

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 focus is on trips entering Beirut during the morning peak. As such, the study area is divided into origin zones (or home ends) 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. Fig. 1 illustrates the map of the study area.

The districts adjacent to the BRT can be described as dense with mixed land use consisting of commercial and residential developments in proximity of each other. Population densities for these zones range from 2000 persons/km^2 (zone 2) to over 15,000 persons/km^2 (zones A and D), largely exceeding the average overall density in Lebanon which falls at around 520 persons/km^2.

The largest portion of demand will be from areas adjacent to the BRT alignment as commuters residing there can easily walk to the transit system and board it to 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 using motorized feeder lines. The interconnectivity ratio, which is a measure of access 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). As such, the study area was bounded based on an interconnectivity ratio of 0.5. The study area was then divided into several origin and destination zones based on typical traffic analysis zones of Lebanon, 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). As seen in Fig. 1, the study area was sub-divided accordingly into 9 origin zones (1 to 9) and 8 destination zones (A to H), with zones 6, 8, and 9 also serving as possible destinations for trips originating at zones 1, 2, or 3.

4.3. Survey and stated preference design

Data was collected by means of a questionnaire tailored for the purpose of this application, with both revealed and stated preferences collected. RP data included accessibility and attitudes towards current public transportation modes, in addition to characteristics of the respondent's typical commute to work/college, including actual travel times and costs. Socio-economic details were also collected alongside questions on familiarity with ridesourcing and attitudinal statements related to cars, existing buses, the proposed BRT system, and ridesourcing.

SP was used for mode choice data as the BRT is not yet operational in Lebanon, and as such RP data related to the BRT does not yet exist. Three hypothetical scenarios were presented to each respondent, and in each scenario respondents were asked to select their preferred travel alternative based on a set of included variables. In every scenario, a BRT trip was divided into three distinct stages: access (residence to BRT boarding station), main transport (boarding BRT station to alighting BRT station), and egress (alighting BRT

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

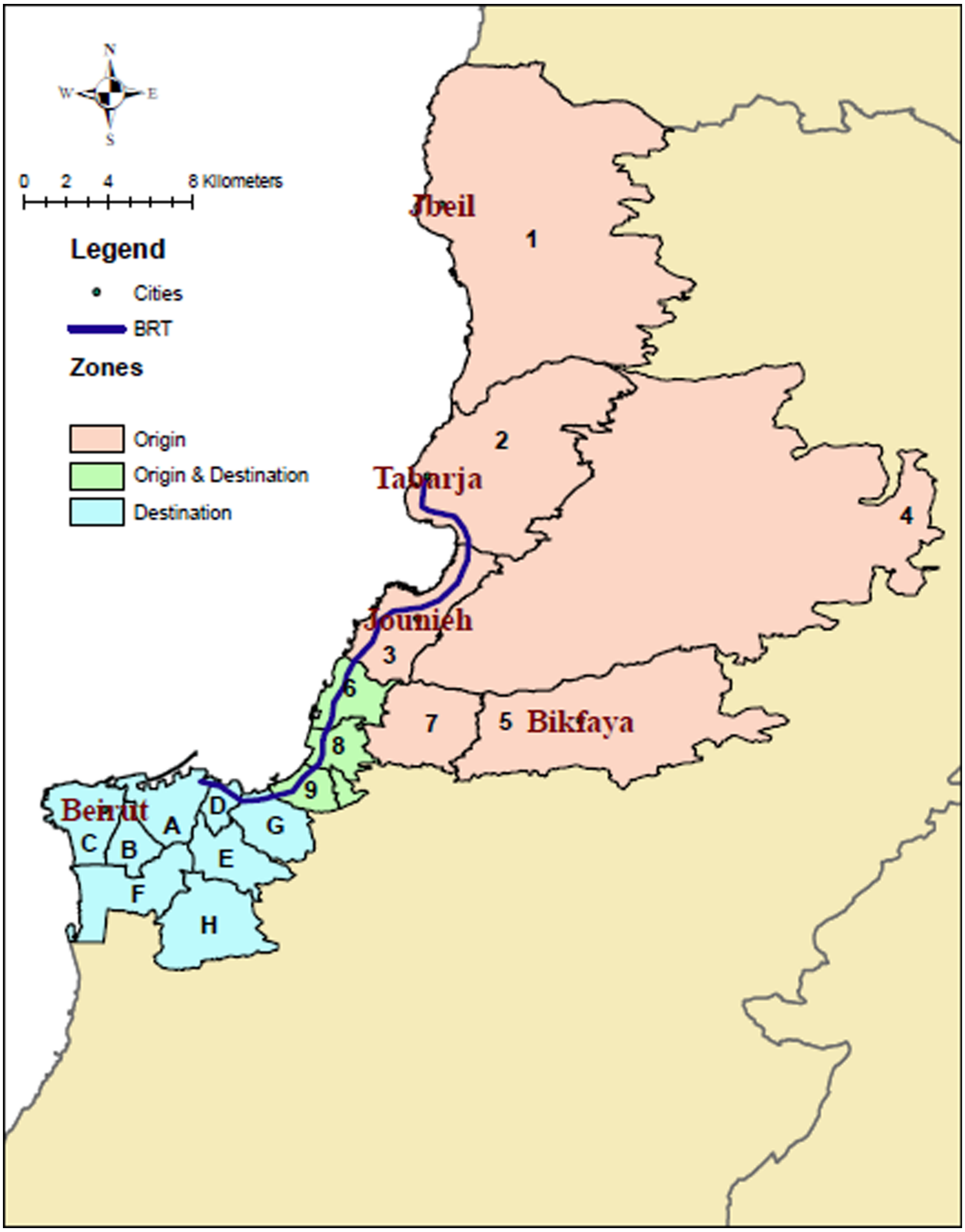

Fig. 1. Study Area.

station to final destination). 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 which is a shared taxi that can pick up and/or drop off passengers at any point along its route (known locally as "service"), 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 private cars.

Presenting all combinations as separate options into a single experiment would lead to complex choice tasks. Therefore, the selection process was divided into three steps (see Fig. 2). In step 1, BRT was fixed as mode of main transport with given attribute levels and the respondent was asked to make two independent selections for the preferred access and egress modes to complete his/her door-to-door trip, assuming BRT was chosen as main mode. Step 2 is a choice confirmation step based on aggregated travel cost

[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.

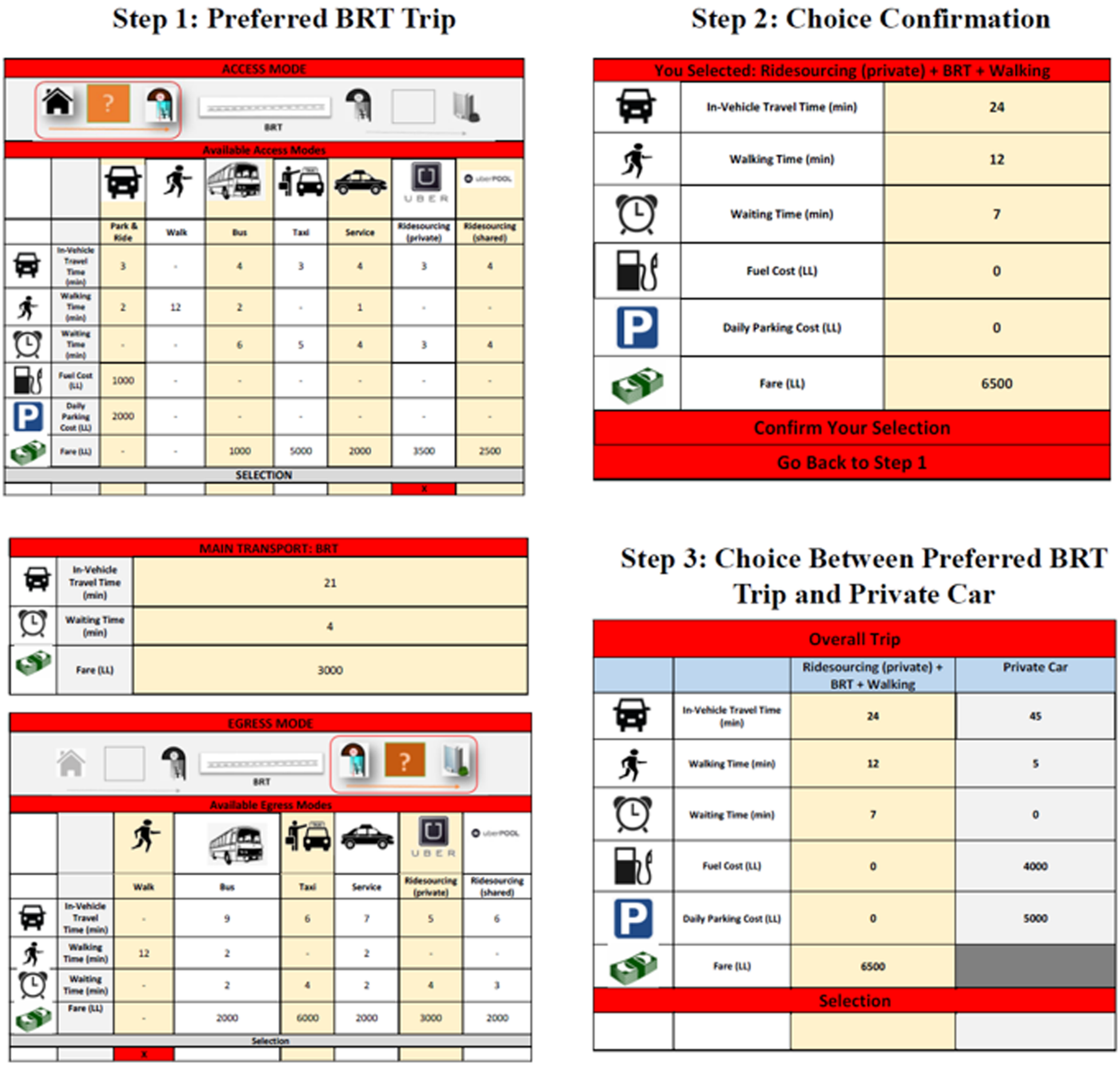

Fig. 2. Overview of a Typical Scenario (LL = Lebanese Lira, where 1 USD = 1500 LL at the time the survey was conducted).

and time components for the overall BRT trip selected in step 1. In step 3, the respondent was asked to choose between the preferred BRT trip selected in the previous two steps and using the car all the way.

For both car and BRT, a unique set of levels was defined for each origin–destination pair to make sure that respondents are presented with realistic values for the attributes of their trip, with 4 levels defined for each attribute. A set of levels for one O-D pair is provided in Appendix A for further reference. Three scenarios were then generated randomly per respondent from the full factorial (see Walker et al., 2018 for a discussion of the random design approach).

4.4. Sampling plan and data collection

A sample size of 400 was adopted. Stratified random sampling was performed based on an exogenous variable defined as the ratio of the door-to-door travel time by car to the expected door-to-door travel time by BRT. Stratified sampling was adopted because different behaviors are expected for different values of the exogenous variable that reflects the attractiveness of the BRT. A large ratio implies 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. Within each stratum, responses are distributed over zones based on population estimates obtained from a local transportation firm.

Data collection was performed in January and February 2019 by a professional survey company. Households within each origin zone were selected randomly. Overall, 400 respondents were interviewed in their homes by trained interviewers, with each respondent receiving 3 different scenarios for a total of 1200 choice experiments.

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%), current 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. Since taxi was not popular as a chosen feeder mode with only 3 and 8 selections for access and egress stages, respectively, out of 1200 scenarios in total, the 8 respondents who chose taxi were eliminated from the data set which reduced the sample size to 392 since it would be difficult to estimate parameters specific to the taxi mode.

Full time workers constitute the dominant majority of the sample while frequent public transportation users (those who use it once a month or more) 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 study. 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 quite deficient.

Around 63% of the sample are male, and around 95% have a high school diploma with 46% having earned a college degree. According to the CIA World Factbook (2019), males constitute around 50.4% of adults in Lebanon which is below the 63% share in the collected sample and may reflect over-representation. However, one explanation for that can be that the gender split in the Lebanese working community is slightly skewed towards males. While no employment data is available, it is reasonable to expect a higher employment rate across men than women as males are still expected to be the main providers for their families in Lebanon.

The age is well distributed over the sample with the largest portion, around 36%, falling between 40 and 49 years. This age category constitutes about 19% of the Lebanese population (CIA World Factbook, 2019) with the slight skew towards older commuters expected as studies reveal that these are more likely to drive than their younger counterparts. The 64+ category is largely under-represented in the sample (around 10.4% of the population) as most people in this category are retired and the study was restricted to active workers.

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 (2007). As for the average household monthly income, over 68% of reported incomes fell below 4,500,000 L.L. (around 3000 USD) while only 7% exceeded 7,500,000 L.L. (around 5000 USD).

Table 1 summarizes the final data set and describes the correlations between different demographic and socio-economic variables and mode choice, notably BRT and ridesourcing usage.

The descriptive 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 public transportation. 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, educational level, and household income do not seem to have a clear impact on main mode choice.

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.

5. Model estimation and results

The discrete choice modeling framework developed in Section 3 is applied using the data collected to model demand for BRT as a main mode and for ridesourcing and other modes as feeders to the planned Beirut BRT. This section covers the assumptions of the application, the model specification, the estimation results, and a discussion of the obtained results.

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

Table 1
Sample Distribution (N = 392) and Correlation between Mode Choice and Different Attributes.

Survey Question	Category	Percentage of Respondents (N = 392)	Percentage of Scenarios where BRT Is Chosen (1176 Scenarios)	Percentage of BRT Users Choosing Ridesourcing**
Household Car Ownership	1	30.61	35.83	36.43
	2	50.26	34.52	43.14
	3	14.29	29.17	55.10
	4	2.81	33.33	45.45
	5+	2.04	54.17	38.46
Public Transportation Usage Frequency	About once a week	6.63	41.03	18.75
	Few times a month	6.12	66.67	39.58
	About once a month	2.30	96.30	53.85
	Several times a year	6.38	34.67	38.46
	About once or twice a year	8.42	50.51	66.00
	Never	70.15	27.17	40.18
Used Ridesourcing Previously	Yes	13.01	45.75	62.86
	No	86.99	32.84	38.10
Flexibility of Work Arrangement	Flexible arrival and departure	8.16	38.54	24.32
	Flexible arrival or departure	26.28	26.54	29.27
	Not flexible	65.56	37.22	48.43
Gender	Male	62.76	26.42	37.44
	Female	37.24	48.17	46.92
Age	18–24	7.91	61.29	47.37
	25–29	13.27	48.72	46.05
	30–39	24.74	45.02	52.67
	40–49	35.71	23.33	30.61
	50–64	17.60	19.81	21.95
	64+	0.77	33.33	66.67
Highest Education Level	Less than high school diploma	4.85	70.18	25.00
	High school diploma	17.35	37.75	36.36
	Technical school	14.54	32.16	40.00
	Some college	17.35	35.29	30.56
	Bachelor degree	42.35	30.12	54.00
	Masters/PhD	3.57	28.57	75.00
Household Size	1	4.08	37.50	61.11
	2	9.44	37.84	50.00
	3	19.13	35.56	47.50
	4	38.27	32.89	35.14
	5	21.94	36.82	37.89
	6+	7.14	23.19	68.75
Monthly Household Income (L.L.*)	0–1,499,999	0.77	55.56	40.00
	1,500,000–2,999,999	31.89	19.47	27.40
	3,000,000–4,499,999	25.51	33.33	31.00
	4,500,000–5,999,999	16.33	48.44	47.31
	6,000,000–7,499,999	4.85	59.65	38.24
	7,500,000–9,999,999	5.10	63.33	55.26
	10,000,000–14,999,999	1.02	25.00	0.00
	I don't know/No answer	14.54	35.09	23.98

* 1 USD = 1500 L.L.
** Using private and/or shared ridesourcing for access and/or egress stages.

trip can skip one of the stages or use multiple modes for access or egress. This assumption allowed to simplify the choice task for participants.

- The alternative specific constant of the car alternative is normalized to zero. The constant of the BRT was also set at zero as the model with three constants per BRT alternative was not estimable. The BRT constant is implicitly incorporated in the constants of the feeders.

5.2. 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:

$$M = \{Car, BRT\}$$

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

Table 2
Explanatory Variables Used in the Model.

Variable	Type	Description
$IVTT^{Z}_{H,n,t}$	Continuous variable	Total one-way in-vehicle travel time by mode H at stage Z for respondent n in scenario t (in hours)
$Walking\_Time^{Z}_{H,n,t}$	Continuous variable	Total one-way walking time by mode H at stage Z for respondent n in scenario t (in hours)
$Waiting\_Time^{Z}_{H,n,t}$	Continuous variable	Total one-way waiting time by mode H at stage Z for respondent n in scenario t (in hours)
$Cost^{Z}_{H,n,t}$	Continuous variable	Cost of one-way trip by mode H at stage Z for respondent n in scenario t (in 1000 L.L.)
$dist_n$	Continuous variable	Total one-way trip distance for respondent n (in km)
$accdist_n$	Continuous variable	One-way access distance for respondent n (in km)
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)
$Flexible_n$	Binary 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.
PT_User_n	Binary variable	A value of 1 indicates that respondent n uses public transportation frequently (at least once a month). A value of 0 indicates otherwise.
$Ride\_User_n$	Binary 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.

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

Several models were tested under different specifications of time and cost variables and with several socio-economic characteristics. The final model selection was performed based on goodness of fit measures, signs of the estimated parameters and significance of the corresponding variables, and value of time analysis. Hybrid choice models, with latent constructs, were also explored to 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.

A 5-fold cross validation test was also performed to assess the predictive power of the various estimated models (Kohavi, 1995). The test consists of splitting the data set into 5 equal sub-sets that are mutually exclusive and collectively exhaustive. Four sub-sets are used for model estimation before applying it on the remaining sub-set to compute the likelihood of replicating the observed choices, with all possible combinations of sub-sets covered. Outlier analysis was finally performed to explore whether additional variables can improve predictive power.

The systematic utilities of the final adopted model are defined as follows, with all explanatory variables defined in Table 2:

$$V'^{Main}_{Car,n,t} = 0 + \beta_{IVTT/\ln(dist)\_Car}\frac{IVTT^{Main}_{Car,n,t}}{\ln(dist)_n} + \beta_{Walking\_Time}Walking\_Time^{Main}_{Car,n,t} + \beta_{Cost,n}Cost^{Main}_{Car,n,t} + \beta_{Age\_Car}Age_n + \beta_{Flex\_Car} Flexible_n + \beta_{PTuser\_Car}PT\_User_n + \omega_{Car,n} \tag{14}$$

$$V'^{Main}_{BRT,n,t} = 0 + \beta_{IVTT\_BRT}IVTT^{Main}_{BRT,n,t} + \beta_{Waiting\_Time}Waiting\_Time^{Main}_{BRT,n,t} + \beta_{Cost,n}Cost^{Main}_{BRT,n,t} \tag{15}$$

$$V'^{Acc}_{Park\,\&\,Ride,n,t} = \alpha_{Park\,\&\,Ride} + \beta_{IVTT/\ln(dist)\_Car}\frac{IVTT^{Acc}_{Park\,\&\,Ride,n,t}}{\ln(accdist)_n} + \beta_{Walking\_Time}Walking\_Time^{Acc}_{Park\,\&\,Ride,n,t} + \beta_{Cost,n}Cost^{Acc}_{Park\,\&\,Ride,n,t} + \omega_{Park\,\&\,Ride,n} \tag{16}$$

$$V'^{Acc}_{Walk,n,t} = \alpha_{Walk} + \beta_{Walking\_Time}Walking\_Time^{Acc}_{Walk,n,t} + \omega_{Walk,n} \tag{17}$$

$$V'^{Acc}_{Bus,n,t} = \alpha_{Bus} + \beta_{IVTT\_BusSer}IVTT^{Acc}_{Bus,n,t} + \beta_{Waiting\_Time}Waiting\_Time^{Acc}_{Bus,n,t} + \beta_{Walking\_Time}Walking\_Time^{Acc}_{Bus,n,t} + \beta_{Cost,n} Cost^{Acc}_{Bus,n,t} + \beta_{PTuser\_BusJitney}PT\_User_n + \omega_{Bus,n} \tag{18}$$

$$V'^{Acc}_{Jitney,n,t} = \alpha_{Jitney} + \beta_{IVTT\_BusSer}IVTT^{Acc}_{Jitney,n,t} + \beta_{Waiting\_Time}Waiting\_Time^{Acc}_{Jitney,n,t} + \beta_{Walking\_Time}Walking\_Time^{Acc}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Acc}_{Jitney,n,t} + \beta_{PTuser\_BusJitney}PT\_User_n + \omega_{Jitney,n} \tag{19}$$

$$V'^{Acc}_{Ride(Pri),n,t} = \alpha_{Ride(Pri)} + \beta_{IVTT\_Ride}IVTT^{Acc}_{Ride(Pri),n,t} + \beta_{Waiting\_Time}Waiting\_Time^{Acc}_{Ride(Pri),n,t} + \beta_{Cost,n}Cost^{Acc}_{Ride(Pri),n,t} + \beta_{Flex\_Ride} Flexible_n + \beta_{Ride\_User}Ride\_User_n + \beta_{Age\_Ride}Age_n + \omega_{Ride(Pri),n} \tag{20}$$

$$V'^{Acc}_{Ride(Sha),n,t} = \alpha_{Ride(Sha)} + \beta_{IVTT\_Ride}IVTT^{Acc}_{Ride(Sha),n,t} + \beta_{Waiting\_Time}Waiting\_Time^{Acc}_{Ride(Sha),n,t} + \beta_{Cost,n}Cost^{Acc}_{Ride(Sha),n,t} + \beta_{Flex\_Ride} Flexible_n + \beta_{Ride\_User}Ride\_User_n + \beta_{Age\_Ride}Age_n + \omega_{Ride(Sha),n} \tag{21}$$

$$V'^{Egr}_{Walk,n,t} = \alpha_{Walk} + \beta_{Walking\_Time} Walking\_Time^{Egr}_{Walk,n,t} + \omega_{Walk,n} \tag{22}$$

$$V'^{Egr}_{Bus,n,t} = \alpha_{Bus} + \beta_{IVTT\_BusSer} IVTT^{Egr}_{Bus,n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Bus,n,t} + \beta_{Walking\_Time} Walking\_Time^{Egr}_{Bus,n,t} + \beta_{Cost,n} Cost^{Egr}_{Bus,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Bus,n} \tag{23}$$

$$V'^{Egr}_{Jitney,n,t} = \alpha_{Jitney} + \beta_{IVTT\_BusSer} IVTT^{Egr}_{Jitney,n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Jitney,n,t} + \beta_{Walking\_Time} Walking\_Time^{Egr}_{Jitney,n,t} + \beta_{Cost,n} Cost^{Egr}_{Jitney,n,t} + \beta_{PTuser\_BusJitney} PT\_User_n + \omega_{Jitney,n} \tag{24}$$

$$V'^{Egr}_{Ride(Pri),n,t} = \alpha_{Ride(Pri)} + \beta_{IVTT\_Ride} IVTT^{Egr}_{Ride(Pri),n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Ride(Pri),n,t} + \beta_{Cost,n} Cost^{Egr}_{Ride(Pri),n,t} + \beta_{Flex\_Ride} Flexible_n + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Pri),n} \tag{25}$$

$$V'^{Egr}_{Ride(Sha),n,t} = \alpha_{Ride(Sha)} + \beta_{IVTT\_Ride} IVTT^{Egr}_{Ride(Sha),n,t} + \beta_{Waiting\_Time} Waiting\_Time^{Egr}_{Ride(Sha),n,t} + \beta_{Cost,n} Cost^{Egr}_{Ride(Sha),n,t} + \beta_{Flex\_Ride} Flexible_n + \beta_{Ride\_User} Ride\_User_n + \beta_{Age\_Ride} Age_n + \omega_{Ride(Sha),n} \tag{26}$$

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 cost parameter is assumed to be randomly distributed to capture unobserved taste variation in cost across individuals (equation (27)), with a log-normal specification to ensure a negative cost coefficient for all individuals (Train, 2009). Time parameters are assumed to be deterministic as their large number requires large computational power when the random specification is adopted. 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 Eq. (28):

$$\beta_{Cost,n} = -e^{(\mu_{\beta Cost,n} + \sigma_{\beta Cost,n} \times \Omega_{Cost,n})} \qquad \Omega_{Cost,n} \sim N(0, 1) \tag{27}$$

$$\omega_{q,n} = \sigma_{\omega_q} \times \Omega_{q,n} \qquad q \in Q = M \cup A \cup E,\ \Omega_{q,n} \sim N(0, 1) \tag{28}$$

$\mu_{\beta_{\text{Cost,n}}}$ and $\sigma_{\beta_{\text{Cost,n}}}$ are, respectively, the mean and standard deviation of the underlying normal parameter across the entire population, with both parameters to be estimated. $\beta_{\text{Cost,n}}$ can be obtained for each individual through simulation.

5.3. 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). Stability was reached at 25,000 draws and the estimation results of the final model are summarized in Table 3.

5.4. Findings and analysis

All level-of-service variables have negative coefficient 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 in-vehicle travel time is always negative but decreases in absolute value 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. The marginal utility of car IVTT is also higher for long trips (i.e. the disutility is lower), for a given IVTT, compared to shorter ones.

Sensitivities for BRT and traditional feeders' IVTT are relatively similar. The marginal disutility of ridesourcing IVTT is higher than that of the BRT which is consistent with the literature (Arentze and Molin, 2013; Yap et al., 2016). This implies that extending the transit corridor and reducing connecting trips result in a better quality of service if other factors are held constant. The coefficients of out-of-vehicle travel time components are more negative than those of in-vehicle travel time, indicating an intuitive additional burden for walking and waiting times. Waiting time is found to be more burdensome 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 are randomly distributed given the log-normal specification of the cost parameter, and are accordingly computed through simulation. In the case of the car, the VOT is also dependent on the logarithm of the total trip distance. Monte Carlo simulation of 1000 instances indicates that the average car value of in-vehicle travel time is $VOT^{Avg}_{Car} = \frac{15,539}{\ln(distance)}$. This translates to around 6744 LL/h for a 10-km trip which is higher than the values of 3928 LL/h (in year 2010 L.L.) found by Danaf et al. (2014), and 5500 LL found by IBI and TEAM (2009). Beyond car users, values of in-vehicle travel time were also derived for the BRT and its feeders with average values obtained in the order of 6212 L.L./h for the BRT, 6077 L.L./h for bus and jitney, and 9101 L.L./h for ridesourcing. Traditional feeders have values of time similar to that of the BRT while that of ridesourcing exceeds the BRT VOT by 46.5%, which is comparable to findings in Sydney from Hensher et al. (2006) about value of time of egress modes exceeding that of

Table 3
Model Estimation Results.

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)	−14.5	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	4.50	0.00
Flexibility (specific to car)	4.79	1.82	2.63	0.01
Flexibility (specific to ridesourcing)	−1.03	0.494	−2.08	0.04
PT User (specific to car)	−5.07	1.88	−2.70	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
$\sigma_{\omega_{Bus}}$	1.24	0.430	−2.89	0.00
$\sigma_{\omega_{Park}}$	3.20	0.637	−5.02	0.00
$\sigma_{\omega_{Ride(Pri)}}$	1.70	0.466	−3.65	0.00
$\sigma_{\omega_{Ride(Sha)}}$	0.989	0.338	−2.93	0.00
$\sigma_{\omega_{Jitney}}$	2.55	0.451	−5.65	0.00
$\sigma_{\omega_{Walk}}$	2.56	0.447	−5.72	0.00
$\sigma_{\omega_{Car}}$	9.46	1.76	−5.36	0.00
Initial Log-Likelihood: −3833.52				
Final Log-Likelihood: −1170.043				
Rho-Squared: 0.694				
Adjusted Rho-Squared: 0.686				
Akaike Information Criterion: 2398.086				
Bayesian Information Criterion: 2545.112				
Final Gradient Norm: +8.914E−05				

the main mode by 61.8%. As for walking and waiting time, their respective average values of time are 19,904 LL/h and 39,160 LL/h and are significantly above the value of in-vehicle travel time, which is consistent with findings from Danaf et al. (2019) where the VOTs of non-motorized and out-of-vehicle travel exceeded that of public transportation IVTT by 97.7% and 54.4%, respectively, based on an application in the Greater Boston Area.

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., 2018a; 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 are 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. Lastly, 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 suggests 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.

6. Forecasting and policy analysis

The selected model was calibrated and then used for forecasting and policy analysis. An origin–destination matrix was obtained for the year 2012 from a local transportation firm and it was subsequently adapted to be compatible with the study area. Demand was forecasted for the year 2019 which is when the current study data was collected even though the date is not that of the BRT launching. Section 6.1 describes the method used for calibration of the constants and Section 6.2 presents policy analysis for a number of scenarios.

6.1. Calibration of the constants

Since the model was estimated using SP data, it cannot be used for forecasting unless the alternative specific constants are re-calibrated based on real market shares (Ben-Akiva et al., 2019; Cherchi and de Dios Ortúzar, 2006) while retaining the trade-offs across variables that are well captured by SP analysis.

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 is performed to reproduce the observed ratio of bus to jitney trips similarly to Glerum et al. (2014), a close BRT share 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. At first, the jitney constant is varied to reach the desired ratio of bus to jitney trips. The second step is to calibrate all constants of feeders to reach a market share for the BRT that is close to that found in other local studies. These two steps 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 as in Table 3 above without any modification, while base values of the attributes are defined to reflect real or anticipated market values (see Appendix B). For step 3, 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 ratio of around 2 is expected for bus to jitney trips as the respective modes are responsible for 12.6% and 6% of total vehicular trips in the Greater Beirut Area (IBI/TEAM, 2009). As for the BRT, a traffic modeling report from a local study predicts a share of 25% for the BRT out of all vehicular trips, compared to 60% for the car and 15% for other public transportation modes (Khatib & Alami/TMS Consult, 2017). Eliminating other transportation modes, and assuming that the ratio of car to BRT trips holds, this translates into a BRT share of 29.41%. Moving to ridesourcing, the market share is not known for Beirut. While its share of total trips in San Francisco reaches 15% during weekday peaks (SFCTA, 2017), its share in most urban cities is closer to 5% (Schaller, 2018). In counties around city cores, shares fall 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). Given international experience to date, we set an endogenous target of 0 to 5% for the share of ridesourcing of total vehicle trips in our study area as a higher share is not to be expected at the launch of the BRT.

Initial forecasts under estimated parameters and constants yield a BRT share of 32.71% and ratio of 0.81 for bus to jitney trips when ridesourcing is assumed to be unavailable as a feeder mode. As true market shares at the BRT launch are not known, the method suggested by Train (2009) for calibrating the constants cannot be used, and a grid search approach is adopted for calibration instead (Liu et al., 2019). The jitney constant is lowered progressively until the desired results are reached. Table 4 summarizes the obtained results.

Results from Table 4 reveal that a jitney constant of −1.5 leads to shares that better reflect the actual market. The BRT share is also close to its desired value and does not need further calibration. Next, ridesourcing is added to the model and constants for its private and shared forms are simultaneously varied until an overall market share falling between 0 and 5% is reached as shown in Table 5.

All three calibration targets are verified in the final model which is then adopted for forecasting and policy analysis. The model and forecasting results are also robust with respect to the market shares that were used for model calibration as only the shares of modes whose constants were varied changed significantly after calibration.

6.2. Policy analysis

Using the model with calibrated constants, the base market shares for this study were forecasted. The sample enumeration method was 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 market shares using the calibrated model are summarized in Table 6. These serve as a benchmark for comparison against different policies of interest.

When ridesourcing was added, the BRT market share increased from 31.68% to 33.53% reflecting possible synergies between the two modes. The shared form of ridesourcing is also dominant over the private form suggesting that integration policies should target enhanced shared rides. In the following sub-sections, market shares are forecasted for different policies as shown in Table 7.

Table 4
Calibration Results of the Jitney Constant.

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

Table 5
Calibration Results under Different Ridesourcing Constants.

($\alpha_{\text{Ride(Pri)}}$, $\alpha_{\text{Ride(Sha)}}$)	Ridesourcing Market Share	Ratio of Bus to Jitney Trips	BRT Market Share
(1.07, 3.33)	8.08%	2.09	34.85%
(0.5, 2.5)	6.68%	2.07	34.23%
(0, 2)	4.85%	2.05	33.53%

Table 6
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	9546	66.47%	
BRT	4816	33.53%	
Access Mode	**Number of Peak Hour Person Trips**	**Percentage of Total Trips**	**Percentage of BRT Trips**
Park & Ride	1314	9.15%	27.29%
Walk	2722	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%
Egress Mode	**Number of Peak Hour Person Trips**	**Percentage of Total Trips**	**Percentage of BRT Trips**
Walk	2696	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%

Table 7
Overview of Policies of Interest.

Policy	Variation Range	Base Values for Trips between Zones 2 and A*
Reduction in Ridesourcing Fares	0% to −50%	5000 L.L. and 3000 L.L. for private and shared ridesourcing, respectively (same for access and egress)
Increase in Car Parking Prices	0–50%	7000 L.L.
Reduction in Feeder Bus Headway	0% to −50%	10 min (Access), 6 min (Egress)
Limited Park and Ride Availability	100–25%	100% (unconstrained availability)
Hybrid Scenario	50% reduction in ridesourcing fare, 50% increase in car parking price, 100% park and ride availability	Same as previous policies

* Values for trips between zones 2 and A are shown as an example for indicative purposes.

6.2.1. Policy 1: Reduction in ridesourcing fare

Adding ridesourcing already revealed that it can induce additional demand for the BRT. This policy further tests the interaction between ridesourcing and BRT by progressively varying ridesourcing fare to get insights on its impact on BRT ridership and understand the potential of possible collaborations. Price reductions can be achieved through subsidies or through additional

Table 8
Forecasting Results for Different Levels of Ridesourcing Fare.

Percentage Change in Ridesourcing Fare						
	0% (Base)	−10%	−20%	−30%	−40%	−50%
Percentage of Total Trips						
Travel Mode						
BRT	33.53%	33.92%	34.42%	35.09%	35.93%	36.89%
Ridesourcing (Access)	3.08%	3.78%	4.59%	5.51%	6.48%	7.42%
Ridesourcing (Egress)	5.66%	6.89%	8.33%	9.92%	11.61%	13.23%

Table 9
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						
Travel Mode						
BRT	33.53%	34.37%	35.22%	36.10%	37.03%	38.05%
Ridesourcing (Access)	3.08%	3.17%	3.26%	3.36%	3.46%	3.57%
Ridesourcing (Egress)	6.63%	6.84%	7.08%	7.35%	7.63%	7.92%

ridesourcing demand and optimal fleet utilization resulting on dense feeder lines that can justify lowering fares while maintaining the desired profit margins. 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. Results are summarized in Table 8.

The applied fare reductions increase market shares for both the BRT and ridesourcing which indicates that a possible collaboration can be beneficial for both parties involved. 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 which offers potential to increase overall market share and revenues from non-BRT trips. As for BRT authorities, a half-reduced ridesourcing fare at the feeder stages is expected to augment BRT market share from 33.53% to 36.89%. Arrangements for such integration can include clauses related to data sharing which benefits transit authorities. 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.

It must be noted that the rates of increase for both ridesourcing and BRT shares are exponential which implies that a policy involving ridesourcing fare reductions is mainly effective for large price drops. Price increases that may result from hikes in demand can also hinder ridesourcing's complementarity effect, with a 40% fare increase reducing its share among feeders by almost 50%.

6.2.2. *Policy 2: Increase in car parking prices*

Incentive zoning is implemented in cities through policies that limit parking availability and dedicate some parking spaces to substitute modes to private cars (carsharing, bikesharing) to promote shared mobility (Cohen and Shaheen, 2018). The reduction in supply may lead to an increase in parking fees. As such, this scenario penalizes the utility of the car alternative by gradually increasing car parking prices 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 9 summarizes forecasting results for car parking prices increasing from 0% to 50% in 10% increments.

For every 10% additional increment in car parking prices, BRT ridership rises by around 0.9% on average based on the range of forecasting. This policy is effective as it incurs no extra costs on transit authorities, while diverging 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 or higher fares for public parking, and by eliminating free curb-side parking.

6.2.3. *Policy 3: Reduction in feeder bus headway*

This policy tests the impact of potential enhancement of traditional feeders on BRT ridership by reducing the headway of feeder buses, and thus, its corresponding 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 10 presents market shares for different feeder bus headways starting with the base value and reaching a decrease of 50% through successive decrements of 10%.

While the impact of this policy on feeder bus ridership is noteworthy, its effect on BRT ridership is minimal as its market share

Table 10
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						
Travel Mode						
BRT	33.53%	33.65%	33.77%	33.90%	34.04%	34.20%
Bus (Access)	1.56%	1.76%	1.98%	2.22%	2.49%	2.78%
Bus (Egress)	5.49%	5.86%	6.25%	6.67%	7.11%	7.58%

Table 11
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				
Travel Mode				
BRT	33.53%	32.64%	31.79%	30.96%
Park & Ride	9.15%	6.26%	4.23%	2.00%
Ridesourcing (Access)	3.08%	3.56%	3.73%	4.00%
Ridesourcing (Egress)	6.63%	6.49%	6.05%	5.86%

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 buses unless the concern is about traffic on local roads. It seems more effective to allocate such funds to subsidies on ridesourcing or other BRT improvements.

6.2.4. Policy 4: Limited Park & ride availability

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 under base conditions. This translates to over 1300 commuters, or over 1000 parking spaces assuming a vehicle occupancy of around 1.2. This parking demand 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 capacity at launch, they state that such capacity is expected to be limited. Therefore, this policy 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 11. 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.

The results indicate that limited park and ride availability negatively affects 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 of 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 the service can cater for over a quarter of BRT customers and over 9% of overall vehicle trips. Existing public parking near 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.

6.2.5. Policy 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%.

Forecasting results reveal that optimal BRT ridership can reach around 6000 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 5000 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.

7. Conclusion

This paper 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. The complementarity between mass transit and ridesourcing is tested, 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 at the feeders stage. An application to the planned Beirut BRT was performed to provide practical insights on the integration potential.

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 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 calibrated model. Results reveal that ridesourcing, especially its shared form, and park and ride widen the target customers of the BRT and help it reach higher ridership levels. The introduction of ridesourcing as feeder augmented the overall market share of the BRT from 31.68% to 33.53%, while a 50% reduction in ridesourcing fare increased the BRT share to 36.89%. BRT demand is highly sensitive to ridesourcing fare demonstrating that a partnership can succeed when pricing algorithms are fitting. Car parking rates also had a major impact on BRT ridership and a price surge hinders 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.

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. Another drawback is the limited sample size. 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. 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 singular trip. The research was also restricted to car users and to commute trips during the peak hour to reduce the number of alternatives and confine the context of the study, while a broader analysis should address users of all modes and other trip purposes.

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 available 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 the access travel time since the locations of these facilities are not yet clearly defined.

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 potential of ridesourcing for door-to-door travel and identify possible competitive trends with fixed alignment transit systems such as the BRT. From a modeling perspective, latent variables can be added to the model, especially for emerging technologies, 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 in 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.

CRediT authorship contribution statement

Najib Zgheib: Formal analysis, Investigation, Methodology, Writing - original draft. **Maya Abou-Zeid:** Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing - review & editing. **Isam Kaysi:** Conceptualization, Investigation, Methodology, Supervision, Writing - review & editing.

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Appendix A. Variables and levels in SP experimental design

Based on the adopted zonal configuration, 81 origin–destination combinations are possible, with each of them having a unique set of levels of the attributes in the SP experimental design, with 4 levels per attribute. The chosen levels cover a range as wide as possible while ensuring that all values remain realistic. 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 (see Tables A1–A3).

Table A1
Variables and Levels for Access Modes for Trips from Zone 7 to Zone A.

Variable	Access Mode*	Level 1	Level 2	Level 3	Level 4
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	1000	1500	2000	3000
	Bus	NA			
	Jitney	NA			
	Taxi	NA			
	Ridesourcing (Private)	NA			
	Ridesourcing (Shared)	NA			
Daily Parking Cost (L.L.***)	Park & Ride	1500	2000	2500	3000
	Bus	NA			
	Jitney	NA			
	Taxi	NA			
	Ridesourcing (Private)	NA			
	Ridesourcing (Shared)	NA			
Fare (L.L.***)	Park & Ride	NA			
	Bus	1000	1500	2000	2500
	Jitney	2000	2500	3000	4000
	Taxi	4000	5000	7000	8000
	Ridesourcing (Private)[1]	3000	4000	5000	7000
	Ridesourcing (Shared)	1500	2500	3000	4000

* 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 = 1500 L.L. at the time the survey was conducted.

[1] Ridesourcing fares were estimated using Careem's fare estimator (https://www.careem.com/en-lb/careem-ride/).

Table A2
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[1]	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	2500	3000	3500	4000
	BRT	NA			
Daily Parking Cost (L.L.)	Car	6000	8000	10.000	12.000
	BRT	NA			
Fare (L.L.)	Car	NA			
	BRT	1500	2000	3000	4000

[1] Two levels reflect potential reductions in car travel time as some commuters switch to the BRT, while another one accounts for the possibility of a slight increase in travel time due to traffic growth and induced demand in case the BRT fails to attract high ridership.

Table A3
Variables and Levels for Egress Modes for Trips from Zone 7 to Zone A.

Variable	Egress Mode*	Level 1	Level 2	Level3	Level4
In-Vehicle Travel Time (min)	Walking	NA			
	Bus	11	13	14	15
	Jitney	10	11	12	13
	Taxi	7	9	10	11
	Ridesourcing (Private)	8	9	10	11
	Ridesourcing (Shared)	8	9	11	12
Waiting Time (min)	Walking	NA			
	Bus	1	2	3	4
	Jitney	1	2	3	4
	Taxi	1	2	3	4
	Ridesourcing (Private)	1	2	3	4
	Ridesourcing (Shared)	1	2	3	4
Walking Time** (min)	Walking	5	7	10	15
	Bus	2	3	4	5
	Jitney	1	2	4	5
	Taxi	NA			
	Ridesourcing (Private)	NA			
	Ridesourcing (Shared)	NA			
Fare (L.L.)	Walking	NA			
	Bus	1000	1500	2000	2500
	Jitney	1000	2000	3000	4000
	Taxi	4000	5000	6000	8000
	Ridesourcing (Private)	2000	3000	4000	5000
	Ridesourcing (Shared)	1000	1500	2000	3000

* 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.

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.

Base values were defined based on GIS analysis, information from Google Maps especially for travel and walking times, and local studies. Ridesourcing fares were guided by fare estimator applications for local ridesourcing operators. Base values from the BRT traffic modeling report were also checked for comparison when applicable (see Table B1).

Table B1
Base Values for Trips between Zones 2 and A.

Base Values	IVTT (min)	Waiting Time (min)	Walking Time (min)	Trips Cost (L.L.)
Main Mode				
Car	88	NA	5	8920
BRT	49	2	NA	4000
Access Mode				
Park & Ride	5	NA	2	5000
Walk	NA	NA	10	NA
Bus	6.5	5	3	1000
Jitney	6	4	3	2000
Ridesourcing (Private)	4.5	2	1	5000
Ridesourcing (Shared)	5.4	2	1	3000
Egress Mode				
Walk	NA	NA	15	NA
Bus	12	3	2	1000
Jitney	11	2	2	2000
Ridesourcing (Private)	9	2	1	5000
Ridesourcing (Shared)	11	2	1	3000

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