Transportation (2020) 47:1733–1763
https://doi.org/10.1007/s11116-019-09973-x

Modeling the choice to switch from traditional modes to ridesourcing services for social/recreational trips in Lebanon

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Published online: 1 February 2019

Abstract

This study investigates the current and potential uptake of ridesourcing services, such as Uber and Careem, by the students of the American University of Beirut, Lebanon. A hybrid choice model is developed to predict the switching choice from traditional modes of transport to ridesourcing services for social/recreational trips made by these students in Lebanon. Data are provided by a web-based survey that includes revealed and stated preferences, besides demographics. It is found that the switching choice is determined by several observed factors, such as door-to-door travel time, waiting time for pick-up, and one-way fares, in addition to a latent variable that captures individual differences in perceptions and attitudes towards ridesourcing services. A base switching probability from traditional modes to ridesourcing services (calculated under a base scenario representing realistic values of the attributes of ridesourcing services if the latter were used to make the most recent social/recreational trip) is estimated to be 0.22. This probability is expected to reach 0.31 under a forecasted policy scenario consisting of 40% reduction in ridesourcing fares. Car users will be more sensitive to switch to ridesourcing services for their social/recreational trips if the ridesourcing fare reduction (40%) is associated with restricted parking conditions consisting of (a) 100% increase of parking fees from actual prices, and (b) 20-minute increase of parking search time and parking time from the actual car travel time. In this case, the resulting switching probability is expected to reach 0.38. By using the estimated choice model to forecast policy scenarios as such, this study can guide planners, policy-makers, and service operators to prioritize effective policies in response to the behavioral change caused by the diffusion of innovative transport services and technologies. The study also contributes to a better understanding of the uptake of ridesourcing services in developing country contexts where public transport services are often inadequate.

Keywords Ridesourcing · Disruptive mobility · Social/recreational trips · Hybrid choice model · Forecasting · Urban transport

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Introduction

With the emergence of new mobility services, innovative transportation choices are offered to travelers. Ridesourcing, carsharing, and ridesharing are examples of recent transformative services and technologies that are moving urban transport towards the sharing economy. By creating new markets and having the potential to replace traditional modes and revolutionize the way people travel, these services are considered “disruptive” mobility alternatives (Meyer and Shaheen 2017). Understanding the impact of these changes on travel behavior can help operators improve the service offerings, and practitioners frame policies and plans to improve the transportation system.

Ridesourcing is a proliferating new transport/business model based on two micro-foundations of urban economies: sharing and matching. It is associated with Transportation Network Companies (TNCs), such as Uber and Lyft, that match passengers with drivers in real-time, commonly via GPS-enabled mobile apps. This new technology system is a car service provided by smartphone apps that enable the users to request a ride and pay for the service (Dawes 2016).

While ridesourcing serves different types of trip purposes (e.g., work, educational, social/recreational, medical, personal business, etc.), ridesourcing services have been mostly used for social/recreational trips (Chen 2015; Rayle et al. 2016; Mahmoudifard et al. 2017), and have been attracting young well-educated users (Rayle et al. 2014, 2016; Chen 2015; Dias et al. 2017).

Uber, an international TNC currently operating in 633 cities (Uber Technologies Inc. 2017a), has pioneered ridesourcing services. Through this app, the user is able to request a ride in real-time from a preset location and preview the fares. When a nearby driver accepts the request, the app displays an estimated time of arrival of the driver heading to the pick-up location, as well as information about the driver to connect with the user. Fares are automatically calculated and charged to the payment method the user has linked to the Uber account. A feedback system is also available to rate the drivers and the riders.

Uber has reached the Middle East (Abu Dhabi, Dubai, Jeddah, Riyadh, and Doha) since 2013 (Uber Technologies Inc. 2017b), and Beirut, Lebanon, in 2014 (Chalfoun 2014). The app is currently operating in Cairo, Dammam, Istanbul, and Manama, as well. Careem, Uber’s twin app in the Middle East, has started operating originally in the United Arab Emirates in 2012, and has expanded regionally to twelve cities, including Beirut (Lemon 2015). Although ridesourcing has been widely studied recently by researchers in the United States (Dawes 2016), specifically in San Francisco (Rayle et al. 2016), Chicago (Uber; Marten 2015; Mahmoudifard et al. 2017), and New York (McKenzie and Baez 2016), and in Asia (Schechtner and Hanson 2017), quantified evidence on the use of ridesourcing services and their impacts has not yet been established in the Middle East, particularly in developing countries, such as Lebanon where public transport is inadequate. This research sheds light on the uptake of ridesourcing services provided by Uber and Careem apps in Lebanon by a young segment of the population. It utilizes revealed/stated preferences and demographics data collected from the students of the American University of Beirut (AUB) by means of a web-based survey, and models the potential switching behavior from traditional transport modes (e.g., bus, taxi, and car) to ridesourcing services, particularly for social/recreational trips. The developed model is a hybrid choice model that integrates a latent variable model (quantifying the attitude towards ridesourcing) and a choice model. Results give insights on the travel behavioral change of the studied segment of the Lebanese population in response to ridesourcing services penetration in the transportation/

business market. The application of the developed model and the forecast of policy scenarios offer insights to operators, planners, and policymakers on how to cope with the behavioral change and guide the transformative mobility.

The remainder of this paper is structured as follows. The second section reviews the literature of ridesourcing including exploratory and behavioral modeling studies. The third section presents a brief overview of the transportation context in Lebanon. The fourth section presents the methodology and data including the survey design, data collection and the sample, in addition to the descriptive analysis results. The fifth section consists of the choice modeling; it provides the model formulation and presents the estimation results with a value of time (VOT) analysis. The sixth section applies forecasting/policy scenarios using the developed model and discusses the findings. The seventh section concludes the paper.

Literature review

Several research studies have addressed the emergence of ridesourcing services as an innovative transportation mode and analyzed the factors influencing the use of these services as well as their implications. This section reviews a number of these studies.

Intercept surveys were conducted in 2014 (Rayle et al. 2016) to explore the use of ridesourcing services in the San Francisco Bay Area. Results showed that these services target mainly young well-educated individuals who prefer travel options with short waiting times and do not like driving. The majority of respondents reported that if ridesourcing services were not available, they would still make the trip using taxi (39%), or transit (33%), while 6% will use their own car.

Perspectives on the revolution of ridesourcing were drawn in Dawes (2016) from a survey conducted in major metropolitan areas of the United States aiming at exploring attitudes towards Uber and Lyft and guiding policymakers in the planning practice. Results showed that 69% of the respondents were ridesourcing users, among them 51% were relying on ridesourcing to avoid driving under intoxication conditions, and 46% were using ridesourcing for social and leisure purposes. Top reasons for using ridesourcing were the service attributes such as convenience and promptness. As for the attitudes towards ridesourcing, 63% of the respondents expressed a positive attitude, while a small percentage (6% of respondents) opposed ridesourcing for ethical and ideological reasons. In addition, more than 25% of the respondents advised a partnership between ridesourcing and public authorities to complement public transit and reduce car ownership. Three logistic regression models were developed. In the first model, the effects of demographics, spatial and transportation characteristics on the usage of ridesourcing were tested. Among demographic variables, only gender, age and education were significant predictors; work trips variable was the only transportation characteristic that significantly influenced the use of ridesourcing, unlike spatial characteristics. The second model used ordered logit whereby the attitude towards ridesourcing was treated as an ordinal dependent variable on a five-point Likert scale. Results of this model showed that the attitude towards ridesourcing is determined by the previous usage of ridesourcing (users, non-users), mode choice (Uber, Lyft), possession of Uber app, gender, and education level. In the third model, a multinomial logit analysis was adopted to predict policy implications for Uber (e.g., forming partnership, regulating). Using Uber, the frequency of use, and the attitudes towards Uber were reported as significant predictors of policy implications. The analysis concluded by deriving a sequential relationship that links demographics to user identification, attitude, and policy implications, therefore, highlighting the importance of studying the individual characteristics.

The impact of demographics and socio-economic variables on the adoption of new on-demand mobility services, including ridesourcing and car sharing, was further determined in Dias et al. (2017) by developing a behavioral choice model. A bivariate ordered probit model was estimated using survey data collected in 2015 by the Puget Sound Regional Council Travel Study which addressed, in addition to socio-economic variables and trip activity characteristics, attitudes, adoption of technology, usage of new mobility services (carsharing and ridesourcing), and potential adoption of autonomous vehicles in the future. More than 85% of respondents reported that they never used ridesourcing. The behavioral choice model integrated latent variables (lifestyle preferences and attitudes). Estimation results showed that employed young people with high education and income levels and who live in dense urban areas are generally the most likely to use ridesourcing services.

A web-based survey, conducted in the Chicago area, asked Uber riders about the transport mode they would choose if Uber was not available (Mahmoudifard et al. 2017). Results showed that among riders who own cars, 54% would drive their own car or use taxi, and the remaining 46% prefer to use public transit instead of Uber. The majority of riders who do not own a car would use public transit (84%) and few will use taxi (16%). The study used this second transport mode choice (in case Uber was not available) and estimated a nested logit behavioral model. Results of this model were used to infer factors that affect the switching choice from car/transit to Uber. Socio-demographic variables (e.g., income, gender, age, and the number of owned vehicles), number of transit stops, access and egress distances of transit, number of transfers for bus, trip purpose and destination, in addition to travel time and cost were found to affect the switching choice.

Discrete choice modeling was used to assess the demand for Uber compared to Chicago Transit Authority (CTA) public transport services by means of a stated preferences survey sent to undergraduate students of Northwestern University (Marten 2015). Three travel situations were offered and respondents were asked to choose the preferred mode of transport between Uber and CTA services. The survey also collected information about the students' demographics and their previous use of both modes. Results showed that the demand for Uber was affected by the differences in travel time and cost between Uber and CTA services, in addition to the previous behavior; no effect was found for the educational status of the students (academic year) and the gender.

Impacts of ridesourcing as an innovative way of travel are not limited to mode choice only. For instance, the influence of the shared mobility, including ridesourcing, on car ownership was addressed by several research studies, such as Grush and Niles (2017); Henao and Marshall (2017); Iacobucci et al. (2017); Rayle et al. (2014) whereby a reduction in car ownership is reported as an expected consequence of using ridesourcing in the long run, in addition to a potential relief in congestion by lowering the number of cars used (Schechtner and Hanson 2017). Moreover, Greenblatt and Shaheen (2015) highlighted the positive effect of ridesourcing on the environment by reducing greenhouse gas emissions due to the reduction in car ownership and the resulting modal shifts towards more sustainable modes such as walking, biking, and carpooling, in addition to the positive effect on the land use associated with the reduction in the demand for parking. The environmental impact of ridesourcing was further evaluated in Carranza et al. (2016) whereby a lifecycle analysis (LCA) was conducted in order to compare ridesourcing services to the use of an owned car. Several cases of travel scenarios were investigated in Los Angeles (e.g., using Uber only, only using Uber with a higher fuel economy, equally alternating between Uber and an owned car, and using an owned car only). Results showed that the least CO_2 emissions were produced by only using Uber with a higher fuel economy scenario, therefore, emphasizing the environmental advantage of using ridesourcing services in terms of reducing air pollution.

To summarize, ridesourcing has been widely studied as a disruptive transformative technology, in the United States particularly. Previous studies revealed that several factors determine the use of ridesourcing, among which are the attributes of the service itself (e.g., travel time, cost), in addition to individual characteristics and socio-demographics (e.g., age, income, educational status). The majority of ridesourcing users were mainly young and well-educated, and ridesourcing trips were essentially social/recreational. Implications of this emergent alternative were found to influence various aspects of travel behavior such as mode choice and car ownership and use, besides its implications on traffic congestion and the environment. To the authors' knowledge, the literature lacks information about the demand for ridesourcing services in the Middle East, where TNCs started recently operating. This study aims at filling this gap by exploring the current and potential uptake of ridesourcing services, particularly by a young educated population in Lebanon, represented by the AUB students, and for social/recreational trips in specific.

Transportation context in Lebanon: a brief overview

The transportation context in Lebanon is characterized by high reliance on private cars (Al-Ayyash et al. 2016). Public transport modes supply 29% of daily trips made by travelers from Greater Beirut which are distributed between jitneys and taxis (19%), and buses/minibuses (10%) (Kaysi et al. 2010). Taxi companies operate based on user phone call requests, while jitney (locally referred to as "service", which is considered a form of shared taxi) responds to variable demand from potential users on the roads where it operates. Buses and minibuses are generally perceived to be inefficient and unreliable with limited coverage. With respect to cost, a ride by bus is cheaper (1000 L.L. or $0.7) than a ride by jitney (2000 L.L. or $1.3) (Danaf et al. 2014). Non-motorized modes (walking and biking) are rarely adopted by travelers because of inadequate infrastructures and conditions (e.g., absence of exclusive bicycle lanes and wide sidewalks) (Al-Ayyash et al. 2016). Because of the high car ownership rate of about 1 car for every 3 persons and the lack of an adequate public transport system, the Greater Beirut Area is characterized by high levels of congestion (Al-Ayyash et al. 2016).

In 2014, two ridesourcing apps penetrated into the transportation market in Lebanon, Uber and Careem (Choquet 2017), thus expanding the modal alternatives available for travelers.

Method and data

This section presents the survey description and design, data collection, sample description, and descriptive statistics.

Survey description and design

Survey sections[1]

The survey consists of five sections. In the first section, available ridesourcing apps (currently running in Lebanon) are presented to respondents. This section gives an overview about Uber and Careem apps, and it is particularly important for respondents who were unaware of the availability of ridesourcing apps in Lebanon or who were unfamiliar with the apps' characteristics.

The second section consists of general questions investigating the awareness about the availability of ridesourcing apps in Lebanon, the possession of a smartphone, and the previous apps usage among AUB students. Users of ridesourcing apps in the last 12 months are asked to indicate the frequency of the app usage, which app is used more often (Uber/Careem), the type of trip for which the ridesourcing app is used more often, and the time of day at which the app is used more often. Then, respondents' attitudes and perceptions towards ridesourcing app attributes (for users based on their prior experience and for non-users based on what they heard/knew about ridesourcing apps) are measured through several attitudinal statements addressing reliability, convenience, safety, modernity, comfort, real time tracking technology, rating system, automatic payment option, etc. By the end of this section, respondents are asked to indicate which factors (from a list) are considered the most when choosing the mode of transport for social/recreational trips. As such, this section aims at providing general insights about the uptake of ridesourcing apps by AUB students as a transportation mode in Lebanon.

The third section consists of revealed preferences (RP) questions related to the last recreational/social trip made in Lebanon. Respondents are asked to indicate the origin/destination of that particular trip, the approximate distance in kilometers "d" between the two locations by choosing one out of five distance ranges ($d<5$, $5\leq d<10$, $10\leq d<20$, $20\leq d<30$, and $d\geq 30$), the approximate door-to-door travel time, the used mode of transport (driving private car (alone), driving private car with other passengers in the car, passenger in a private car, bus, taxi, service, Uber/Careem, walk, bike, motorcycle, and other), and the one-way fare. For the considered trip, drivers of a private car (alone) are also asked parking-related questions (if any) such as fees, type of parking (valet or other), and parking searching time. Additionally, drivers of a private car with other passengers in the car, and passengers in a private car are asked questions clarifying the total number of individuals present in the car during that particular trip and the share of costs (fuel and parking fees, if any). Taxi riders are asked to indicate the total number of passengers in the taxi cab during that particular trip, as well as the approximate waiting time for pick-up from the origin location. Riders of Uber/Careem are also asked about the waiting time for pick-up, in addition to the reasons for choosing ridesourcing for that particular trip.

The fourth section consists of four stated preferences scenarios only addressed to drivers of a private car (alone), drivers of a private car with other passengers in the car, passengers in a private car, bus, taxi, and service. In each one, the respondent is asked whether he/she would like to switch from his/her actual mode of transport to ridesourcing (Uber/Careem) for that particular social/recreational trip considered in the previous section. Each scenario differs by the values of the following variables for ridesourcing: (1) the door-to-door travel time by ridesourcing, (2) the waiting time for pick-up since the request of the taxi or Uber/

[1] The questionnaire is available from the authors upon request.

Careem, and (3) the one-way fare of ridesourcing. An example of the four scenarios as presented to the respondents in the survey is illustrated in Fig. 1.

The fifth section collects socio-demographic information including gender, age, nationality, current educational status, Faculty, current residence location, and the approximate family monthly income range.

Scenario design

The four hypothetical scenarios are presented to respondents depending on the market segment to which they belong, given their responses to the questions of the third section. Each market segment is defined by the distance range (five ranges are considered, as stated previously), the actual RP mode of transport (car, bus, service, and taxi are considered), and the parking conditions (valet parking or other) for the car mode which consists of driving a private car alone, driving a private car with other passengers in the car, and passenger in a private car. As such, twenty-five market segments are considered in the survey scenario design.

As for the variables of interest, the door-to-door ridesourcing travel time is presented as the product of the actual travel time, as indicated by the respondent in the third section, by a ratio with four possible levels for each market segment, allowing for travel time variation with respect to the distance range and the mode of transport. The one-way ridesourcing fare is presented with four possible levels at each market segment independent of the RP mode but varying across the distance range. The waiting time for pick-up is presented with four possible levels at each market segment similarly for the car, bus, and service users. However, for a taxi user, the presented time for pick-up is the product of the actual time for pick-up, as indicated by the respondent in the third section, and a ratio with four possible levels. The waiting time for pick-up and the ratio levels vary across the distance range.

The market segments, the variables of interest and their levels are shown in Table 8 in "Appendix 1". Given the levels by market segment, four scenarios (or profiles) are randomly generated for each respondent from the full factorial. The robustness of the random design compared to other experimental design approaches has been demonstrated in Walker et al. (2017).

Scenario 1: Please consider the following scenario.

	Ridesourcing (Uber/Careem)	**Actual Mode (Service)**
Door-to-Door Travel Time	26 min	35 min
Waiting Time for Pick-up	3 min	N/A
One-Way Fare	7000 L.L.	4000 L.L.

* Considering Scenario 1, would you switch to ridesourcing for making that particular social/recreational trip?

◯ Yes ◯ No

Fig. 1 An example of the four scenarios as presented to the respondents in the survey

Data collection and sample description

The survey was web-based and was implemented using the LimeSurvey platform at AUB. It was launched in June 2017 and remained active till July 2017. It targeted 3300 randomly selected AUB students (a random list of emails was provided to the authors by the university administration, to whom an invitation to take the survey was sent). The invitation to take the survey indicated that this is a research study about transportation mode choice for recreational/social trips in Lebanon and students' willingness to use real time app-based mobility service or ridesourcing, such as Uber and Careem. A total of 540 students took the survey; however, only 271 students totally completed it, resulting in a response rate of 8.2%. It should be noted that the majority of the students who took the survey and did not complete it did not reach the revealed preferences section (i.e., did not go beyond the second section of the survey). The survey might have been perceived as too long by those students. After data cleaning, the responses of 41 students were removed because of inaccurate answers on several questions (e.g., travel time, trip distance range, parking fees, one-way fare), resulting in unrealistic scenarios in the stated preferences section. Therefore, the remaining sample consisted of 230 students, 51% of whom are females and 49% are males. Most of them (63%) are aged between 18 and 22. The average family monthly income of the respondents is 7,500,000 L.L. (Lebanese Liras) ($5000), and the median value is 5,000,000 L.L. ($3300). Forty-seven percent of the respondents did not report their family monthly income range. The majority of the respondents live in Beirut and Mount Lebanon. Table 1 summarizes demographics of the final sample considered for analysis. It should be noted that the sample of the respondents is not representative of the AUB students' population in terms of the educational status and the Faculty. Therefore, weights are used in forecasting as discussed later.

Descriptive statistics

Data obtained from the general section of the survey are summarized in Table 2. The majority of the surveyed students (89%) are aware of the availability of ridesourcing apps in Lebanon. While all respondents own a smartphone, 45% of them have used ridesourcing for making trips in Lebanon. Six percent of the app users did not use ridesourcing in the last 12 months in Lebanon, fifty percent of the users have used ridesourcing only few times (1–10 times), while twelve percent have used ridesourcing three or more times per week, and the remaining others have used ridesourcing services either once every month, or once every week, or twice every week. Uber app is used more often (78%) than Careem app (22%) for making trips in Lebanon. By trip purpose, the highest share of ridesourcing trips is for social/recreational (42%), followed by educational trips (22%) and personal business trips (18%), while 8% of the trips are for going to work, 1% of the trips are for shopping, and 9% are for other purposes. The survey also shows that ridesourcing is used more during daytime (56%). The relatively high usage during night time (44%) may be attributed to the operating hours of buses in Lebanon (most of which stop running after 8 PM with a few exceptions) and to the greater sense of safety in a taxi at night compared to a bus. The most considered factors when choosing the mode of transport for social/recreational trips were mainly travel cost, convenience, safety, and waiting time for pick-up.

Table 3 summarizes some characteristics of the last social/recreational trip considered in this survey. Those are derived from the revealed preferences section. Forty-six percent of the surveyed students reported that their last trip door-to-door travel time was shorter

Table 1 Demographics of the final sample

Variable	Frequency (Freq.)	Percent (%)
Gender		
Male	113	49
Female	117	51
Total	230	100
Age		
18–22	144	63
23–25	53	23
26–30	27	12
31 or above	6	2
Total	230	100
Educational status		
Undergraduate	140	61
Graduate	90	39
Total	230	100
Faculty		
Faculty of Agriculture and Food Sciences	4	2
Faculty of Arts and Sciences	33	14
Maroun Semaan Faculty of Engineering and Architecture	140	61
Faculty of Medicine	5	2
Faculty of Health Sciences	4	2
Rafic Hariri School of Nursing	1	0
Suliman S. Olayan School of Business	43	19
Total	230	100
Nationality		
Lebanese	168	73
Dual Nationality Lebanese	48	21
Foreigner	14	6
Total	230	100
Monthly family income range		
0–2,000,000 L.L.	12	5
2,000,000–4,000,000 L.L.	34	15
4,000,000–6,000,000 L.L.	22	9
6,000,000–8,000,000 L.L.	18	8
8,000,000–10,000,000 L.L.	18	8
10,000,000–15,000,000 L.L.	7	3
15,000,000–30,000,000 L.L.	10	4
More than 30,000,000 L.L.	2	1
I don't know/I prefer not to answer	107	47
Total	230	100

than 30 minutes, while 22% reported that their last trip took more than one hour. The major mode of transport used to make the last social/recreational trip is the car mode (53%), followed by Uber/Careem (23%). While the frequency of the ridesourcing usage shown in

Table 2 General section statistics

Variable	Freq.	%
Awareness of ridesourcing apps		
Yes	204	89
No	26	11
Total	230	100
Smartphone ownership		
Yes	230	100
No	0	0
Total	230	100
Ridesourcing use in Lebanon		
Yes	103	45
No	127	55
Total	230	100
Frequency of use (last 12 months)		
I didn't use ridesourcing in the last 12 months	6	6
Few times (1–10 times)	51	50
Once every month	10	9
Once every week	14	14
Twice every week	10	9
3 or more times per week	12	12
Total	103	100
App		
Uber	76	78
Careem	21	22
Total	97	100
Trip purpose		
Educational	21	22
Work	8	8
Social/recreational	41	42
Shopping	1	1
Personal business	17	18
Medical	0	0
Other	9	9
Total	97	100
Time of use		
Day	54	56
Night	43	44
Total	97	100
Most considered factor for choosing the mode of transport (social/recreational trips)		
Travel cost	104	45
Door-to-door travel time	21	9
Waiting time for pick-up	23	10
Ability to do other things during the travel	5	2
Convenience	30	13
Comfort	14	6
Safety	29	13

Table 2 (continued)

Variable	Freq.	%
Other	4	2
Total	230	100

Table 3 Revealed preferences section statistics (for the last social/recreational trip)

Variable	Freq.	%
Distance range		
d < 5 km	56	24
5 km ≤ d < 10 km	52	23
10 km ≤ d < 20 km	34	15
20 km ≤ d < 30 km	24	10
d ≥ 30 km	64	28
Total	230	100
Mode		
Driving private car (alone)	47	20
Driving private car with other passengers in the car	52	23
Passenger in a private car	24	10
Bus	10	4
Service	19	8
Taxi	11	5
Uber/Careem	53	23
Walk	6	3
Bike	1	0.5
Motorcycle	1	0.5
Other	6	3
Total	230	100

Table 2 seems to be relatively low (35% of those who have used ridesourcing before use it at least once per week), about half of respondents who have used ridesourcing for making trips in Lebanon reported to use it for the last social/recreational trip as shown in Table 3 (53 users out of 103 students who have used ridesourcing services in Lebanon). While we have no explanation for this difference, studies such as Rayle et al. (2016) have reported that the highest percentage of ridesourcing trips was for the social/leisure purpose (67%). The majority of ridesourcing trips (79%) were for short distances [shorter than 5 km (47%) or ranging between 5 and 10 km (32%)].

We also analyze the main factors that might lead people to choose ridesourcing services. For the last social/recreational trip considered in the revealed preferences section of the survey, respondents were asked: *Why did you choose ridesourcing for that particular trip? Please indicate your level of agreement with the following statements*. These statements were related to the attributes of ridesourcing services (e.g., cost, travel time, waiting time for pick-up), public transport availability and accessibility, car ownership, attitude towards driving, and parking (cost, availability). We observe the following:

- Ridesourcing users reported a relatively positive attitude towards the service by rating more positively statements addressing ridesourcing attributes (e.g., ridesourcing is cheaper, faster than other modes).
- The highest percentages of the actual ridesourcing users who agree/strongly agree with the stated reasons were for the following two statements: (1) *The waiting time for pick-up is short with ridesourcing* (72%), and (2) *Ridesourcing is faster than other modes* (66%). Therefore, we conclude that the main causes of using ridesourcing services are the short waiting time for pick-up and the overall short travel time. This finding confirms that the "natural" attributes of ridesourcing services, mainly the waiting time for pick-up and the travel time, have the greatest appeal for the actual users of these services.

Among the surveyed students, 163 students were subjected to the stated preferences section that includes the four hypothetical scenarios (excluding students who have used Uber/Careem, walk, bike, motorcycle and other as they constitute a minor percentage of the used modes of transport).

Since the invitation to participate in the survey mentioned ridesourcing services, we further investigate the possibility of self-selection bias, i.e., whether those who are actually interested in ridesourcing were more willing to take the survey or not. We note that:

- The percentage of respondents who have never used ridesourcing to make trips in Lebanon is 55%.
- Among surveyed students who were subjected to the stated preferences section, the percentage of respondents who did not choose ridesourcing in any of the four scenarios is 52%. This indicates that there is a fraction of the respondents who do not seem to be interested in ridesourcing.
- We also further analyze the responses to the attitudinal statements and report for every statement the percentage of respondents who have a negative attitude (strongly disagree or disagree with the statement) or neutral attitude (neither agree nor disagree with the statement) towards ridesourcing. We denote the percentage of these respondents P_0 and present the results in Table 4. This analysis indicates that not all of the respondents are necessarily enthusiastic about ridesourcing.

Table 4 Percentage of respondents with negative or neutral attitude towards ridesourcing (P_0)

Statement	P_0 (%)
I can count on ridesourcing to get me to my destination on time	30
Ridesourcing is a convenient mode of transport for me	39
Ridesourcing is safe	39
Ridesourcing makes me feel modern	46
Ridesourcing is comfortable	33
I like the technology platform based on real time tracking in ridesourcing	11
I like the rating system available after the trip in ridesourcing	26
I like the automatic payment option (using credit or debit cards) in ridesourcing	29
I would like to use ridesourcing in bad weather conditions	24
I would like to use ridesourcing to avoid driving when intoxicated	24

Based on the above, we believe that referring to ridesourcing (Uber and Careem) in the recruitment message did not affect the decision whether to take part of the survey or not, and therefore, did not affect the randomness of the sample nor bias the results.

Choice modeling

This section presents the model formulation (framework and specification), and the estimation results.

Model formulation

Model framework

In order to study the willingness of the AUB students (who didn't report using ridesourcing for their last social/recreational trip in Lebanon) to use ridesourcing, an econometric model is developed based on the results of the stated preference (SP) and revealed preference (RP) survey. The proposed modeling framework (Fig. 2) consists of a hybrid choice model (Ben-Akiva et al. 2002; Walker and Ben-Akiva 2002) that integrates a latent variable model, quantifying unobserved variables, with a discrete choice model, capturing the respondent's decision whether to switch or not from the actual RP mode to ridesourcing, based on observed exogenous variables (socio-demographic/individual characteristics and scenario variables), in addition to the latent variable. The following subsections formulate the two components of the proposed model and the likelihood function.

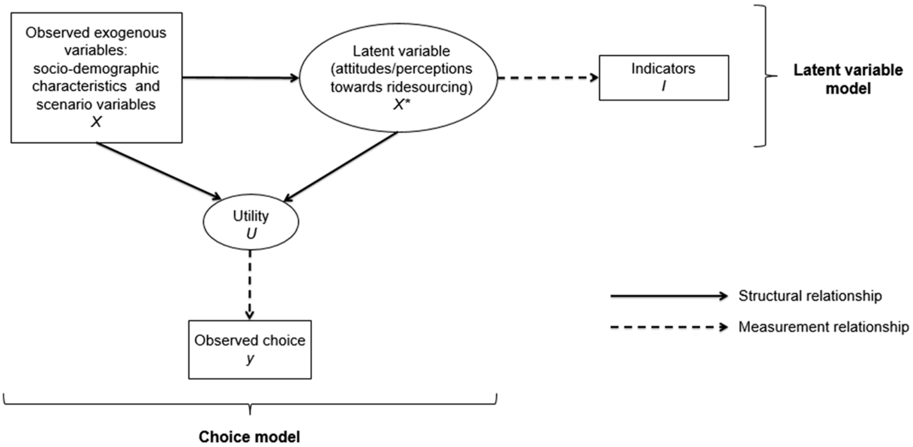

Fig. 2 Framework of modeling the switching choice from the actual mode of transport (RP) to ridesourcing (observed variables are shown in rectangles and latent variables are shown in ellipses)

Latent variable model

It is assumed that the switching decision-making process from the RP mode to ridesourcing is influenced by attitudes/perceptions towards ridesourcing as an unobserved factor. This is captured through a latent variable model within the hybrid choice model. Note that for some respondents the attitude is based on actual experience using ridesourcing while for those who have not used the service the attitude is based on the perceived attributes of the service based on what they have heard or know. In either case, the attitude is expected to be associated with the willingness to use ridesourcing. Psychometric data measuring the attitude towards ridesourcing are obtained through respondents' stated level of agreement with several attitudinal and perceptual statements used as indicators of the latent variable, implying a measurement relationship (dashed arrow between the indicators and the underlying latent variable). The ridesourcing latent variable can be expressed as a function of the respondent's individual characteristics (such as gender and income); an initial model with socio-demographic variables included in the structural equation of the latent variable was tested but their impact was not statistically significant at the 95% level of confidence. Therefore, the latent variable is treated as exogenous and is defined as follows (Eq. 1):

$$RLV_n = \eta_n \tag{1}$$

where RLV_n is the ridesourcing latent variable for individual n, and η_n is a random disturbance term which is independently and identically distributed (iid) as normal and can be expressed as in Eqs. (2) and (3) below:

$$\eta_n \sim N(0, \sigma_\eta^2) \tag{2}$$

$$\eta_n = \sigma_\eta * \Omega_n \tag{3}$$

where σ_η is the standard deviation of the η, and Ω is the standardized normal form of η, i.e., $\Omega \sim N(0,1)$.

Since the data used in this study are stated preferences collected at one point in time, the direction of causality between the attitude and the choice behavior cannot be confirmed. The latter would require repeated choices collected over time for every individual in order to model how attitudes are shaped by experience and how they influence subsequent choices. This is especially important for current non-users or infrequent users of ridesourcing as their reported attitudes may not be stable. However, we believe it is reasonable to assume that the attitude towards ridesourcing is likely to influence the choices one makes in an SP context. Incorporating the attitude in the choice model did not seem to bias the coefficients as they are very comparable to the coefficients of a model with just an individual-specific random term (without an attitude and its indicators) that does not vary over choice scenarios. Both models (the integrated choice-latent variable model and the choice model with the individual-specific random term) did not result in any substantially different level of service/value of time parameters.

The respondents' level of agreement with the attitudinal/perceptual statements is stated on a scale from 1 (strongly disagree) to 5 (strongly agree). In order to identify which of these statements are better correlated with the switching behavior, a statistical analysis was conducted using t-test on each indicator whereby respondents are divided into two groups: (1) respondents who agree or strongly agree with the statement about using ridesourcing, with an average switching choice M_1 over the four scenarios (1 if switch; 0 if don't switch), and (2) respondents who disagree, strongly disagree, or neither agree nor disagree with the statement about using ridesourcing, with an average switching choice M_0. A comparison between the two groups was done to test if the respondents who agree or strongly agree with the statements about using ridesourcing (which are positively phrased) are more likely to switch to ridesourcing. Results of this analysis are presented in Table 5. Accordingly, the most three correlated indicators with the switching behavior (I_2, I_4, and I_7) are selected and included in the measurement equations of the latent variable.[2]

The measurement equation is expressed as follows (Eq. 4).

$$I_{r,n} = \lambda_{RLV,r} * RLV + \upsilon_{r,n}; \quad r = 2, 4, 7 \tag{4}$$

where $I_{r,n}$ represents the normalized survey response of individual n for the indicator r, that is, the survey response on each of the statements is deviated from its sample mean value in order to eliminate the constants in the measurement and structural equations of the latent variable. The indicators are assumed to be continuous variables for simplicity. $\lambda_{RLV,r}$ is the factor loading to be estimated, and $\upsilon_{r,n}$ is a measurement error term that is iid normal (Eq. 5).

$$\upsilon_{r,n} \sim N(0, \sigma^2_{\upsilon_r}) \tag{5}$$

The value of $\lambda_{RLV,2}$ is fixed to 1 in order to set the scale of the latent variable *RLV*.

Choice model

The developed choice model is a binary choice between two alternatives: switch/not switch from the RP mode to ridesourcing. One model is formulated for all RP transport modes. The model assumes that the respondent's choice depends on the observed exogenous variables as well as the latent variable, and it is based on the random utility maximization theory, i.e., the respondent will choose the alternative that provides the maximum utility. The structural equation of the utility of each of the two alternatives, shown in Eqs. (6) and (7), comprises the systematic utility, and a random disturbance. The systematic utility depends on observed variables denoted as *X*, including the scenario variables (door-to-door travel time, waiting time for pick-up, and one-way fares), the previous use of ridesourcing services in Lebanon, and the actual RP mode (as a dummy variable), in addition to the ridesourcing latent variable.

$$\begin{aligned} U_{switch\,(n,t)} = {} & ASC + \beta\_BUS * bus + \beta\_SERV * service + \beta\_TAXI * taxi \\ & + \beta_{TT} * deltaTT_t\_scaled + \beta\_WTt * deltaWT_t\_scaled * taxi \\ & + \beta\_WTo * WT_t\_RIDEscaled * other + \beta\_FARE * deltaFARE_t\_scaled \\ & + \beta_{use} * PUse + \beta\_RLV * RLV + \varepsilon_{switch(n,t)} \end{aligned} \tag{6}$$

$$U_{don't-switch(n,t)} = 0 + \varepsilon_{don't-switch(n,t)} \tag{7}$$

The index t denotes a choice scenario ($t = 1, 2, 3, 4$) and the β's are parameters to be estimated. The ASC is an alternative specific constant for the switch alternative. Table 6 shows the definitions of the variables and random disturbance terms in Eqs. (6) and (7).

[2] Other considerations for selection of which statements to include in the measurement equations of the latent variable were used, such as benchmarking the resulting VOT with other local estimates (e.g., a model with all indicators was tested; however, the obtained VOT was significantly higher than that previously estimated for AUB students).

Table 5 Results of the statistical analysis on attitudinal and perceptual statements (indicators)

Designation	Attitudinal and perceptual statements (manifest variable)	M_1	M_0	*p* value
I_1	I can count on ridesourcing to get me to my destination on time	0.28	0.25	0.28
I_2	Ridesourcing is a convenient mode of transport for me	0.32	0.21	0.02
I_3	Ridesourcing is safe	0.27	0.28	0.57
I_4	Ridesourcing makes me feel modern	0.30	0.23	0.11
I_5	Ridesourcing is comfortable	0.29	0.24	0.20
I_6	I like the technology platform based on real time tracking in ridesourcing	0.26	0.32	0.77
I_7	I like the rating system available after the trip in ridesourcing	0.29	0.23	0.16
I_8	I like the automatic payment option (using credit or debit cards) in ridesourcing	0.24	0.33	0.93
I_9	I would like to use ridesourcing in bad weather conditions	0.28	0.24	0.27
I_{10}	I would like to use ridesourcing to avoid driving when intoxicated	0.26	0.24	0.34

Table 6 Definitions of variables in the utility equations

Term	Definition
Bus	Dummy variable, is equal to 1 if the RP mode is bus and is equal to 0 otherwise
Service	Dummy variable, is equal to 1 if the RP mode is service and is equal to 0 otherwise
Taxi	Dummy variable, is equal to 1 if the RP mode is taxi and is equal to 0 otherwise
$DeltaTT_t\_scaled$ *(hours)*	Scaled difference in the door-to-door travel time between ridesourcing and the RP mode at scenario *t*; $\Delta TT = TT_{ridesourcing} - TT_{RPmode}$
$DeltaWT_t\_scaled$ *(hours)*	Scaled difference in the waiting time for pick-up between ridesourcing and the taxi mode; $\Delta WT = WT_{ridesourcing} - WT_{taxi}$
$WT_t\_RIDEscaled$ *(hours)*	Scaled waiting time for pick-up for ridesourcing if the RP mode is different from taxi (at scenario *t*)
Other	Dummy variable, is equal to 0 if the RP mode is taxi and is equal to 1 otherwise
$DeltaFARE_t\_scaled$ *(L.L./10,000)*	Scaled difference in the one-way fare at scenario *t* between ridesourcing and the RP mode; $\Delta FARE = FARE_{ridesourcing} - FARE_{RPmode}$
PUse	Dummy variable characterizing the previous usage of ridesourcing, is equal to 0 if the individual has never used ridesourcing, and is equal to 1 if the individual has previously used ridesourcing
$\varepsilon_{switch(n,t)}$	Random disturbance term of the switching alternative for individual *n* at scenario *t*, iid Extreme Value Type I (0,1)
$\varepsilon_{don't-switch(n,t)}$	Random disturbance term of the non-switching alternative for individual *n* at scenario *t*, iid Extreme Value Type I (0,1)

The panel (agent) effect is accounted for in this model by using the same value of the attitude for a given individual across choice scenarios.

The measurement equation of the choice is represented as follows:

$$y_{n,t} = \begin{cases} 1 & \text{if } U_{switch(n,t)} \geq U_{don't-switch(n,t)} \\ 0 & \text{if } U_{switch(n,t)} < U_{don't-switch(n,t)} \end{cases} \tag{8}$$

where $y_{n,t}$ is the choice made by individual n at scenario t.

Likelihood function

The maximum likelihood technique is used to estimate the unknown parameters. The resulting joint probability f of the observed endogenous variables y and I, conditional on the exogenous variables X, in the four scenarios, is given by Eq. (9) below.

$$f\left(y_1, y_2, y_3, y_4, I_n | X_n\right) = \int_{\Omega} \prod_{t=1}^{4} P(y_{n,t} | X_{n,t}, RLV_n) * h\left(I_n | RLV_n\right) * g\left(\Omega_n\right) d\Omega \tag{9}$$

where I_n is a vector of indicators for person n, and X_n is a matrix of observed variables for person n over all choice scenarios.

The functional forms of the different probability components are given by Eqs. (10 a and 10 b), (11) and (12) below.

$$P(y_{n,t} = 1 | X_{n,t}, RLV_n) = \frac{e^{\left(ASC + \beta_{RLV} RLV_n + \beta_X X_{n,t}\right)}}{1 + e^{\left(ASC + \beta_{RLV} RLV_n + \beta_X X_{n,t}\right)}} \tag{10 a}$$

$$P(y_{n,t} = 0 | X_{n,t}, RLV_n) = \frac{1}{1 + e^{\left(ASC + \beta_{RLV} RLV_n + \beta_X X_{n,t}\right)}} \tag{10 b}$$

$$h\left(I_n | RLV_n\right) = \prod_{r=2,4,7} \frac{1}{\sigma_{\upsilon_r}} \emptyset \left[\frac{I_{r,n} - \lambda_{RLV,r} * RLV_n}{\sigma_{\upsilon_r}} \right] \tag{11}$$

$$g\left(\Omega_n\right) = \emptyset\left[\Omega_n\right] \tag{12}$$

where $g\left(\Omega_n\right)$ is the density function of Ω_n which is given by the standard normal density function Ø.

Model estimation results

The proposed integrated model is estimated simultaneously in Python Biogeme (Bierlaire and Fetiarison 2009; Bierlaire 2016) using a maximum likelihood estimator and numerical integration. Estimation results are shown in Table 7.

As expected, cost and time parameters have negative signs indicating that one is more likely to switch if the ridesourcing travel time, waiting time, and cost are smaller than those of the current mode. For the ridesourcing waiting time for pick-up variable (WT_RIDEscaled) considered with different RP modes than taxi (e.g., bus, car, service), as it increases, the switching utility decreases. All scenario variables are statistically significant at the 95% level of confidence, except for the difference in the waiting time for pick-up considered with taxi RP mode (deltaWT_scaled). The non-significance of this factor could be here attributed to the trip purpose considered in this study as the model is developed for social/

Table 7 Model estimation results

Choice Model				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
Switching constant (ASC)	-0.293	0.634	-0.46	0.64
deltaTT_scaled (min/60)	-1.79	0.824	-2.17	0.03
deltaWT_scaled (min/60)	-10.5	12.2	-0.86	0.39
WT_RIDEscaled (min/60)	-5.46	2.15	-2.54	0.01
deltaFARE_scaled (L.L./10,000)	-1.36	0.461	-2.94	0.00
Bus	-2.87	2.37	-1.21	0.23
Service	0.114	0.646	0.18	0.86
Taxi	0.396	1.77	0.22	0.82
PUse	-0.502	0.663	-0.76	0.45
RLV	9.30	4.20	2.21	0.03
Latent Variable Model				
	Parameter Estimate	**Robust Standard Error**	**Robust t-test**	**p-value**
Factor Loadings				
λ_{I2}	1.00	-	-	-
λ_{I4}	0.466	0.269	1.73	0.08
λ_{I7}	0.455	0.227	2.00	0.05
Standard Deviations of Error Terms				
σ_n	0.305	0.121	2.52	0.01
σ_{υ_2}	0.897	0.0581	15.46	0.00
σ_{υ_4}	0.891	0.0524	17.01	0.00
σ_{υ_7}	0.758	0.0477	15.88	0.00
Model Statistics				
Final Log-Likelihood	-897.19			
Choice Log-Likelihood	-120.65			
Final Gradient Norm	+3.33e-06			

recreational trips where short waiting time for pick-up is not as critical as for other trip purposes such as work or educational trips. Though the coefficients of the RP mode variables (bus, service, and taxi) are not significant, their magnitudes and signs can give insights about which market segments are more likely to switch to ridesourcing compared to the car mode (considered here as base). Taxi riders are more likely to switch to ridesourcing than service users who are also more likely to switch to ridesourcing than the users of the car mode. Bus users are less likely to switch to ridesourcing than car users. The latent variable parameter is positive and statistically significant at the 95% level of confidence, indicating that a more positive attitude towards ridesourcing leads to a higher probability of switching to ridesourcing (the attitude captures the perceptions of convenience of ridesourcing, the rating system of the apps, and how modern one feels using ridesourcing). The factor loadings of the indicators in the latent variable model are statistically significant at the 90% level of confidence demonstrating the validity of the attitudinal and perceptual statements in measuring the latent variable. All standard deviations of the error terms are statistically significant at the 95% level of confidence.

Dividing the estimated travel time parameter by the estimated one-way fare parameter shows that AUB students' value of time (VOT) is around 13,200 L.L./h ($9 per hour). Applying an inflation rate of 4%, the calculated VOT will be equivalent to approximately 10,000 L.L./h in year 2010 L.L., which is in accordance with the findings of a previous study that modeled the travel choices of AUB students (Danaf et al. 2014) and estimated a VOT of 10,144 L.L./h ($7 per hour) for AUB students in year 2010 L.L.

It should be noted that several specified models were tried; however, the presented model is adopted based on the significance of the estimated coefficients, the choice log-likelihood (reflecting goodness-of-fit), and the VOT analysis.

Model application

This section uses the developed discrete choice model to forecast policy scenarios and discusses their implications on the switching behavior from traditional modes to ridesourcing services for social/recreational trips. We suggest three policy scenarios based on the current transportation context in Lebanon characterized by inefficient public transport, high rates of auto ownership, and parking problems (scarcity and high cost). We also analyze the effects of each scenario and all scenarios combined on the switching decision. This policy analysis aims to guide operators, planners, and policymakers on how to best integrate ridesourcing into the existing transportation system and ensure their potential effective role.

Forecasting scenarios

Base scenario

In order to test the effect of changes in the transportation alternatives offered to the traveler on the probability of switching to ridesourcing, a base scenario is first designed, in which a reasonable level of each scenario variable is suggested based on actual values of ridesourcing attributes in Lebanon while also matching the characteristics of the respondent's last social/recreational trip, as reported in the RP section of the survey (e.g., the trip distance range and origin). That is, for each individual, the base scenario consists of actual values of one-way fare, door-to-door travel time, and waiting time for pick-up if ridesourcing services (Uber/Careem) are used to make that particular trip. Actual values are derived from the pricing model adopted by the TNCs in Lebanon, and considering door-to-door travel times under base conditions. For the waiting time for pick-up, the base value depends on the trip origin to account for differences in the concentration of the ridesourcing services in the different cities of Lebanon. Base scenario levels are presented in Tables 9 and 10 of "Appendix 2". Given this base scenario, the hybrid choice model presented above is applied to the survey sample using sample enumeration (Ben-Akiva and Lerman 1985; Train 2009) to simulate individual switching probabilities. It should be noted that in order to calculate the aggregate average switching probability, weights are applied to the individual switching probabilities since the sample is not representative of the AUB students' population. Weights are calculated by market segment by dividing the number of AUB students in that market segment by the number of survey respondents in the same segment. Data about the former are obtained from the AUB Fact Book (OIRA-AUB 2017). Market segments are classified by gender, student status (i.e., undergraduate or graduate), and Faculty (all seven AUB Faculties are considered).

Simulation results of the base scenario show that the weighted aggregate switching probability is 0.22. Moreover, the simulation shows that taxi users (who have chosen the taxi mode for their last social/recreational trips) are the most likely to switch to ridesourcing services with 63% of taxi users willing to switch under the base scenario conditions, followed by service users (34%), then car users (16%), while bus users are the least likely to switch to ridesourcing services (15%). These results are consistent with the interpretation of the estimated coefficients in the previous section. Further, ridesourcing trips were also found in Rayle et al. (2016) to replace taxi trips essentially, as the largest number (39%) of ridesourcing users who would still make the trip if ridesourcing services were not available said that alternately they would choose to ride a taxi. From a trip distance range perspective, simulation results of the base scenario show that the percentage of individuals willing to switch from the current RP mode to ridesourcing services increases when the trip distance range decreases (e.g., a switching percentage of 36% is obtained for trips shorter than 5 km, while a switching percentage of 12% is obtained for trips longer than 30 km) indicating that ridesourcing mainly attracts short distance trips. A similar conclusion is also found in Chen (2015) where ridesourcing trips were generally shorter in distance than trips using traditional modes.

Policy scenarios

Scenario 1—reducing ridesourcing fares In the first scenario (Fig. 3), the impact of decreasing ridesourcing one-way fares is tested. Decreases of 10%, 20%, 30%, and 40% from the suggested base one-way fares are forecasted. Results show that the aggregate switching probability from the current RP mode to ridesourcing services increases from 0.22 (under the base scenario conditions) to 0.31 after applying a decrease of 40% to the one-way fare of ridesourcing services.

Scenario 2—increasing parking fees The second scenario (Fig. 4) tests the effect of increasing the parking fees on the switching probability, particularly from the car mode to ridesourcing services. Increases of the RP parking fees by up to 100% are tested, and values of the ridesourcing attributes are those of the base scenario. Results show that the

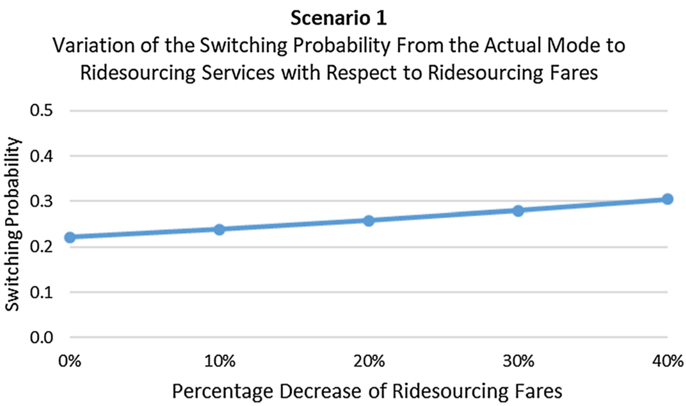

Fig. 3 Forecasting the effect of decreasing ridesourcing fares

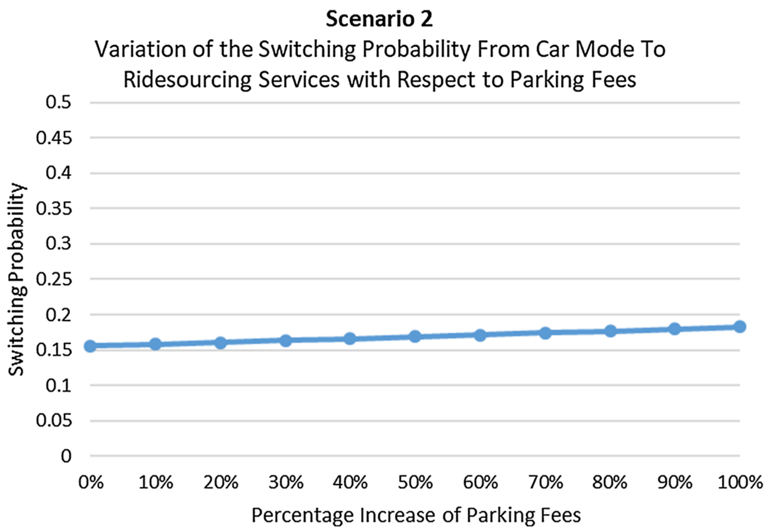

Fig. 4 Forecasting the effect of increasing parking fees

aggregate switching probability from the car mode to ridesourcing services increases from 0.16 (under the base scenario conditions) to 0.18 if parking fees are doubled.

Scenario 3—increasing car travel time The third scenario (Fig. 5) tests the effect of spending additional time to search for parking and park if the car mode is used to make the trip. Increases of 5, 10, 15, and 20 minutes on the actual RP car door-to-door travel time are tested for all car users regardless of the actual type of parking (valet parking or other).

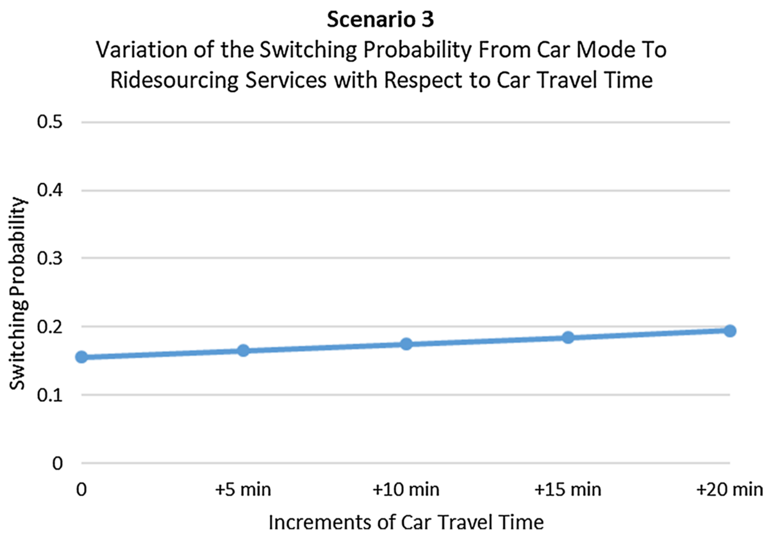

Fig. 5 Forecasting the effect of increasing the car travel time

Results show that the aggregate switching probability from the car mode to ridesourcing services increases from 0.16 (under the base scenario conditions) to 0.19 if additional 20 minutes are spent to search for parking and park the car.

Combining policy scenarios We further forecast and analyze the effect of combining the three scenarios on the choice to switch from the traditional mode to ridesourcing services by simultaneously varying the levels of the three considered scenario variables. We represent graphically the weighted average switching probability (displayed in colors) as a function of scenario variables (displayed on the three axes). The percentage decrease of ridesourcing fares is designated by the variable x, the percentage increase of parking fees is designated by the variable y, and the increment of car travel time (in minutes) is designated by the variable z. The weighted average switching probability is estimated for a total of 9261 different combinations of levels of scenario variables (obtained by combining 21 different levels of the three scenario variables). Figure 6 shows the resulting plot as viewed from different angles.

Results of this analysis show that decreasing the percentage of ridesourcing fares scenario, taken separately (for y = z=0), has the largest effect on the average switching probability, followed by increasing the car travel time scenario (for x = y=0), then increasing the percentage of parking fees scenario (for x = z=0). The graphical presentation (Fig. 6) also

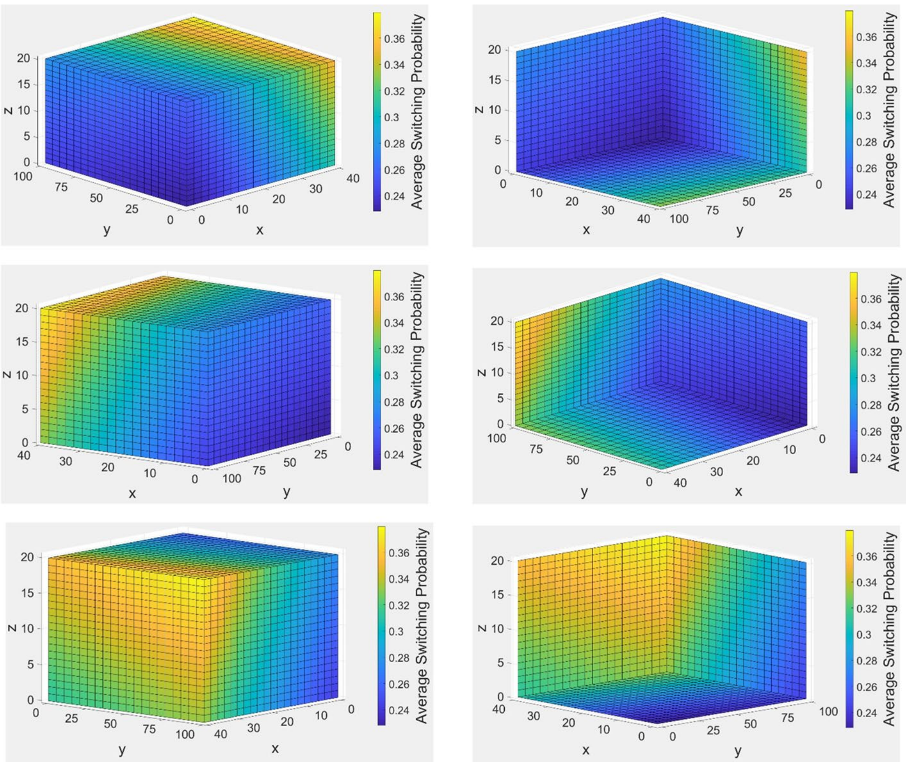

Fig. 6 Plot of the weighted average switching probability as a function of scenario variables as viewed from different angles (x is the percentage decrease of ridesourcing fares, y is the percentage increase of parking fees, and z is the increment of car travel time in minutes)

shows that the combination of the highest levels of the three scenario variables (x = 40, y = 100, z = 20) generates the highest average switching probability (0.38); this point corresponds to the yellow color of the upper end of the color bar.

Discussion

Impacts of policy scenarios

Given the current stage of ridesourcing diffusion in Lebanon, the weighted aggregate probability of actually using ridesourcing services for the last social/recreational trip is 0.25 as derived from the RP section's results. The additional potential (e.g. due to increase in awareness about the service) of using ridesourcing is captured through the aggregate switching probability simulated under the base scenario and is found to be 0.22. This shows that AUB students (and other similar young educated population groups) are a fairly good target as users of ridesourcing services in Lebanon for social/recreational trips, and are open to this emerging transformative transportation technology.

The comparison between the three forecasted policy scenarios, each considered separately, shows that the largest effect on the overall switching probability from the current mode to ridesourcing services is observed when lower ridesourcing prices are in effect. For instance, Fig. 6 shows that the overall switching probability from the traditional RP mode to ridesourcing services reaches 0.24 when the parking fees are doubled (second scenario with x = 0, y = 100, z = 0), and 0.25 when the car travel time is increased by 20 minutes (third scenario with x = 0, y = 0, z = 20), while it reaches 0.31 with a 40% price reduction (first scenario with x = 40, y = 0, z = 0). Therefore, when ridesourcing fares decrease due to greater diffusion of the service and/or potential subsidies offered by the university to students, this will have a great impact on students' adoption of the service. Currently, the difference between the actual fares of ridesourcing services and taxi is not very significant in Lebanon (particularly for short distance trips), which leaves ridesourcing in the class of expensive transport modes in Lebanon. For instance, a trip from the American University of Beirut (AUB) to ABC Achrafieh Mall, Beirut (of approximately 4.8 km) costs with a traditional taxi cab operating in Lebanon (e.g., Allo Taxi) 12,000 L.L. ($8) (Allo Taxi 2017), 6000–10,000 L.L. ($4–7) with UberX, an economic option of Uber (Uber Technologies Inc. 2017c), and 10,000 L.L. ($6.6) with Careem (2017). Therefore, when ridesourcing fares become lower, this will enhance the perception of ridesourcing as a relative "low cost taxi service" and further encourage its adoption in Lebanon.

Parking difficulty and prices are reported in Mahmoudifard et al. (2017) to be main causes of the shift from the car mode to ridesourcing services. Nevertheless, the second and third scenarios, each considered separately, show that the switching probability from the car mode to ridesourcing services is not very sensitive to car parking price (scenario 2; Fig. 4) or search time (scenario 3; Fig. 5), with both scenarios reflecting the actual parking situation in Beirut and its neighborhood characterized by high parking fees and turnover rates (Aoun et al. 2013). As such, it seems that car users have some inertia/resistance to switch from the car mode to ridesourcing services, even under hard and constrained conditions of car use. While results of the study by Rayle et al. (2016) indicate a possible reduction of car use and ownership thanks to ridesourcing services, such implications cannot be expected from the second and third scenarios as tested separately in this study. This could be attributed to the attachment of AUB students to the car as a mode of transport, for social/recreational trips particularly, to the extent that lower car levels of service do not cause a significant shift away from that modality style. Such attachment goes back to the car ownership and use concept as a rooted ideology in Lebanon, particularly for AUB students who mainly come from wealthy families and as a young population segment often perceive the car as a status symbol (Aoun et al. 2013; Belgiawan et al. 2014). This is in contrast to trends in developed countries where social norms about car ownership may be less ingrained in the culture, and together with better public transport systems and mobility services, reduce the need/desire to own a car among younger people (Belgiawan et al. 2014). Another reason could be associated with the fact that ridesourcing services are not yet very widely spread in Lebanon; therefore, larger shifts might be observed once they become more popular. Furthermore, Fig. 6 shows that a wide variation in the color range (from the blue to the orange/yellow) is observed on the plane orthogonal to the plane (y, z) implying a significant variation in the average switching probability when x varies for different levels of y and z. Particularly, as levels of y and z increase, the sensitivity to switch increases with variations in x. This implies that car users might become more sensitive to switch from the car mode to ridesourcing services for their social/recreational trips if exacerbated driving conditions such as high parking fees and extensive time to search for parking and park are associated with a decrease of ridesourcing fares.

Limitations and recommendations

Though the forecasted policy scenarios do offer insights to operators, planners, and policymakers on the factors that cause the switching behavior from traditional transport modes to ridesourcing services, the study implications may not be generalized for the following reasons.

First, the ridesourcing level-of-service variables considered in this study depend on the extent to which ridesourcing services are spread out in Lebanon, therefore, they are endogenous. That is, the levels of ridesourcing attributes may change with a significant variation (increase or decrease) in the expansion of these services in the future. For instance, we suggested the levels of ridesourcing fares for the base scenario according to the pricing model actually adopted by the TNCs in Lebanon. However, such prices are unstable as they may increase or decrease depending on the fluctuations in demand and supply of ridesourcing services. This is also the case for the waiting time for pick-up attribute. Therefore, the simulation results for the base scenario are specific to the levels considered in this study. For the same reason, one may argue that when the number of users will increase—as a result of the diffusion of the service—the price will be automatically reduced without the need of any policy intervention. Such endogenous relation between the price and demand may not immediately produce effective and significant price drop in a relatively short period, knowing that ridesourcing services are still at an early stage of emergence in Lebanon. We highlight that the policy scenario of reducing ridesourcing fares suggested in this paper (scenario 1), aims to test the effect of an external/exogenous intervention on demand. Encouraging the switching choice from traditional modes to ridesourcing services by making the latter more attractive, as done in scenario 1, would expedite their wide diffusion among other modes of transportation in Lebanon.

Second, the study is based on SP data derived from a survey that targeted AUB students particularly, and thus, the results of the developed choice model and its application are only valid to this population characterized by different travel patterns and mode choices when compared to the general Lebanese population (Danaf et al. 2014). A larger survey that extends to the general population is needed to evaluate the impact of ridesourcing services in Lebanon, as a developing country of the Middle East, on a larger scale.

Third, the choice model developed in this study focuses only on social/recreational trips and therefore the study findings are limited to this particular trip purpose. If daily educational/work trips are to be considered in the travel patterns, for example, increasing the door-to-door travel time for the car mode might lead to different switching probability from the car mode to ridesourcing services from that predicted here for social/recreational trips in which additional time spent to park can be tolerated in favor of other considerations (case of the third scenario of this study).

Fourth, the developed model is not able to predict the effect of an improvement in the attributes of the traditional modes, e.g., reduction in bus travel time, on the mode choice behavior. A consequence of such improvement may be the switch from ridesourcing services to the bus alternative for the actual users of ridesourcing services, thus, resulting in a reduction in the RP sample of the actual users of Uber/Careem apps; however, the presented model lacks the capability of predicting such switching behavior. A more generalized mode choice model that caters for the different modes available for a decision-maker in Lebanon is required to forecast total market shares.

To this end, planners and policymakers should cautiously consider additional implications when addressing services provided by Uber and Careem apps in Lebanon. Though ridesourcing is perceived negatively by some as unfairly competing with traditional modes of transport, mainly with taxi (Rayle et al. 2016), the relatively lower cost provided by ridesourcing services would expand the choices available for a traveler who wishes to make a trip in a cab that offers convenience and comfort, but does not afford to pay excessively high fares. This competition would also be beneficial as it might result in improving taxi attributes, mainly the waiting time for pick-up, in response to the reduced waiting time for pick-up provided by ridesourcing. Policymakers should also consider the contribution of ridesourcing in complementing and empowering public transit in Lebanon. Rayle et al. (2016) highlight this effective role of ridesourcing in a travel context characterized by a shortage of public transit which is the case of Lebanon where bus services are inefficient (Aoun et al. 2013). Platforms such as UberPOOL and UberHOP have the potential to play this role (Lewis and MacKenzie 2017). In 2015, the Philippines became the first country in Asia to regulate ridesourcing services nationwide, and to legally frame the operations of TNCs, widening therefore the opportunities of the transportation system to move towards innovative safe technologies and leading to economic vitality (Schechtner and Hanson 2017). In September 2017, the Minister of Investment and International Cooperation in Egypt has announced Uber public bus to serve all Egypt's Governorate once the regulations for Uber are officially issued (Hassanin 2017). Policymakers in Lebanon should also consider such initiatives of cooperation with Transportation Network Companies to prioritize effective and collaborative policies aiming to improve mobility in Lebanon.

Conclusion

In this study, a quantitative choice analysis of a disruptive on-demand app-based transport technology is presented. An integrated choice model with a latent variable is developed to quantify the switching choice from traditional transport modes (e.g., car, bus, taxi, and service/jitney) to ridesourcing services in Lebanon (Uber and Careem apps) for social/

recreational trips. A web-based survey was conducted with students in the American University of Beirut (AUB) to collect revealed preferences (RP), stated preferences (SP) data, and demographics of the AUB students. The RP section of the survey asked the students about their last social/recreational trip made in Lebanon, while the SP section offered four hypothetical choice scenarios and asked the respondents about their willingness to switch from the actual mode (RP) to ridesourcing services in each scenario under different conditions of travel time, waiting time for pick-up, and one-way fares. The latent variable consists of attitudes and perceptions towards ridesourcing services and explains individual differences among AUB students. It is found that the switching decision from traditional modes to ridesourcing services is significantly affected by the differences in door-to-door travel time and one-way fares between ridesourcing and the traditional mode, ridesourcing waiting time for pick-up, and the latent variable.

The model simulation results show that taxi riders are the most likely to shift to ridesourcing services and the switching choice is most likely to occur with short trip distances. The estimated choice model is used to forecast policy scenarios. Results show that lower ridesourcing fares attract AUB students to use the ridesourcing for their social/recreational trips, while inadequate driving conditions (e.g., increased parking fees, increased parking search time and parking time) do not significantly refrain them from using the car mode and switching to ridesourcing services for their social/recreational trips. However, under conditions of reduced ridesourcing fares combined with constrained driving conditions, car users will be more likely to switch from the car mode to the ridesourcing services. A better understanding of the factors affecting the switching choice from traditional modes of transport to ridesourcing services can help operators improve their services. The study also highlights implications of ridesourcing in terms of complementing the existing transportation services in Lebanon, and guides planners and policymakers towards collaborative practices with Transportation Network Companies in order to make use of emerging technologies and further contribute to a sustainable multimodal urban transport in Lebanon.

Acknowledgements The authors thank all the students that answered the survey and three anonymous reviewers for their valuable feedback.

Authors' contribution RT: Literature review, survey design, descriptive analysis, modeling, manuscript writing. MA-Z: Overall coordination, guidance on survey design and modeling, manuscript editing

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Appendix 1

See Table 8.

Table 8 Market segments (M_i), variables of interest, and their levels

Distance	Mode	Condition	M_i	Ratio of travel time (min)				Ridesourcing one-way fare (L.L.)[a]				Waiting time for pick-up (min)			
d < 5 km	Car	Valet parking	M_1	1.25	0.95	0.81	0.75	4000	6000	9000	11,000	2.00	4.00	10.00	15.00
		Other parking	M_2	0.87	0.72	0.64	0.58	4000	6000	9000	11,000	2.00	4.00	10.00	15.00
	Bus		M_3	0.68	0.50	0.42	0.30	4000	6000	9000	11,000	2.00	4.00	10.00	15.00
	Service		M_4	0.80	0.65	0.55	0.46	4000	6000	9000	11,000	2.00	4.00	10.00	15.00
	Taxi		M_5	1.27	0.96	0.82	0.72	4000	6000	9000	11,000	0.08[b]	0.14[b]	0.22[b]	0.30[b]
5 ≤ d < 10 km	Car	Valet parking	M_6	1.26	0.94	0.79	0.69	7000	10,000	12,000	16,000	3.00	6.00	12.00	16.00
		Other parking	M_7	0.85	0.70	0.61	0.54	7000	10,000	12,000	16,000	3.00	6.00	12.00	16.00
	Bus		M_8	0.60	0.45	0.36	0.27	7000	10,000	12,000	16,000	3.00	6.00	12.00	16.00
	Service		M_9	0.74	0.60	0.52	0.48	7000	10,000	12,000	16,000	3.00	6.00	12.00	16.00
	Taxi		M_{10}	1.24	0.97	0.90	0.86	7000	10,000	12,000	16,000	0.13[b]	0.20[b]	0.28[b]	0.32[b]
10 ≤ d < 20 km	Car	Valet parking	M_{11}	1.20	0.91	0.84	0.74	13,000	15,000	18,000	23,000	5.00	9.00	13.00	17.00
		Other parking	M_{12}	0.88	0.71	0.62	0.53	13,000	15,000	18,000	23,000	5.00	9.00	13.00	17.00
	Bus		M_{13}	0.58	0.43	0.33	0.26	13,000	15,000	18,000	23,000	5.00	9.00	13.00	17.00
	Service		M_{14}	0.72	0.59	0.51	0.45	13,000	15,000	18,000	23,000	5.00	9.00	13.00	17.00
	Taxi		M_{15}	1.24	0.93	0.86	0.80	13,000	15,000	18,000	23,000	0.15[b]	0.24[b]	0.31[b]	0.35[b]
20 ≤ d < 30 km	Car	Valet parking	M_{16}	1.15	0.92	0.83	0.73	20,000	25,000	32,000	36,000	7.00	11.00	14.00	18.00
		Other parking	M_{17}	0.86	0.70	0.61	0.54	20,000	25,000	32,000	36,000	7.00	11.00	14.00	18.00
	Bus		M_{18}	0.55	0.40	0.30	0.24	20,000	25,000	32,000	36,000	7.00	11.00	14.00	18.00
	Service		M_{19}	0.70	0.54	0.47	0.42	20,000	25,000	32,000	36,000	7.00	11.00	14.00	18.00
	Taxi		M_{20}	1.15	0.98	0.87	0.80	20,000	25,000	32,000	36,000	0.16[b]	0.27[b]	0.34[b]	0.38[b]
d ≥ 30 km	Car	Valet parking	M_{21}	1.14	0.96	0.88	0.75	30,000	40,000	52,000	65,000	8.00	13.00	17.00	20.00
		Other parking	M_{22}	0.84	0.71	0.60	0.50	30,000	40,000	52,000	65,000	8.00	13.00	17.00	20.00
	Bus		M_{23}	0.52	0.40	0.28	0.23	30,000	40,000	52,000	65,000	8.00	13.00	17.00	20.00
	Service		M_{24}	0.67	0.56	0.48	0.41	30,000	40,000	52,000	65,000	8.00	13.00	17.00	20.00
	Taxi		M_{25}	1.15	0.93	0.82	0.77	30,000	40,000	52,000	65,000	0.17[b]	0.29[b]	0.36[b]	0.40[b]

[a] 1500 L.L. is equivalent to 1 USD

[b] Indicates ratio of the waiting time for pick-up (in case of the taxi as actual mode of transport)

Appendix 2

See Tables 9 and 10.

Table 9 Ratio of ridesourcing to current RP mode travel time and ridesourcing one-way fare for the base scenario

Distance	Mode	Condition	Segment (M_i)	Ratio of travel time (min)	Ridesourcing one-way fare (L.L.)
d < 5 km	Car	Valet parking	M_1	1.00	7000
		Other parking	M_2	0.70	7000
	Bus		M_3	0.45	7000
	Service		M_4	0.60	7000
	Taxi		M_5	1.00	7000
5 ≤ d < 10 km	Car	Valet parking	M_6	1.00	11,000
		Other parking	M_7	0.68	11,000
	Bus		M_8	0.40	11,000
	Service		M_9	0.58	11,000
	Taxi		M_{10}	1.00	11,000
10 ≤ d < 20 km	Car	Valet parking	M_{11}	1.00	17,000
		Other parking	M_{12}	0.67	17,000
	Bus		M_{13}	0.38	17,000
	Service		M_{14}	0.54	17,000
	Taxi		M_{15}	1.00	17,000
20 ≤ d < 30 km	Car	Valet parking	M_{16}	1.00	28,000
		Other parking	M_{17}	0.65	28,000
	Bus		M_{18}	0.36	28,000
	Service		M_{19}	0.53	28,000
	Taxi		M_{20}	1.00	28,000
d ≥ 30 km	Car	Valet parking	M_{21}	1.00	45,000
		Other parking	M_{22}	0.64	45,000
	Bus		M_{23}	0.35	45,000
	Service		M_{24}	0.52	45,000
	Taxi		M_{25}	1.00	45,000

Table 10 Waiting time for pick-up by ridesourcing modes as function of the trip origin for the base scenario

Trip origin	Waiting time for pick-up (min)
Municipal Beirut (MB)	5
Greater Beirut (GB), outside MB	10
Outside GB	15

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