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Does ride-hailing increase or decrease vehicle kilometers traveled (VKT)? A simulation approach for Santiago de Chile

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ABSTRACT
Many authors have pointed out the importance of determining the impact of ride-hailing (ride-sourcing) on vehicle kilometers traveled (VKT), and thus on transport externalities like congestion. However, to date there is scant evidence on this subject. In this paper we use survey results on Uber use by residents of Santiago, Chile, and information from other studies to parameterize a model to determine whether the advent of ride-hailing applications increases or decreases the number of VKT. Given the intrinsic uncertainty on the value of some model parameters, we use a Monte Carlo simulation for a range of possible parameter values. Our results indicate that unless ride-hailing applications substantially increase average occupancy rate of trips and become shared or pooled ride-hailing, the impact is an increase in VKT. We discuss these results in light of current empirical research in this area.

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Ride-hailing; ridesourcing; sharing economy; taxi; transportation network companies

1. Introduction

Ride-hailing can be defined as profit motivated on-demand ride services through a smartphone application, as opposed to nonprofit ride-sharing or car-pooling services and traditional taxi services. As summarized by Henao (2017), in the literature there are several names to refer to ride-hailing platforms, such as ridesourcing, app-based ride services, ride-booking, on-demand rides, commercial transport apps and transportation network companies (TNCs), among others. The advent of ride-hailing technologies is rapidly changing the urban mobility patterns and the passenger transport industry in many cities around the world. Regulators in many jurisdictions are grappling with the legal and policy implications of these new services as they clearly violate existing taxi regulations but are nonetheless highly valued by users.

Ride-hailing services raise many issues including their impact on passenger safety, universal accessibility requirements, insurance liability, driver labor protection and privacy of information. Ride-hailing is also an opportunity to improve service quality, mobility and the incidence of "driving while intoxicated" (DWI) felonies.[1] In many large cities with already high congestion levels, the impact of ride-hailing applications on vehicle kilometers or miles traveled (VKT or VMT) is of paramount importance.

In general, a key to understand the effect of ride-hailing applications on transportation externalities is to estimate which modes are being substituted. An analysis of the most common cases will illustrate these ideas. When comparing ride-hailing with traveling with one's own car, there are two arguments by which ride-hailing platforms can reduce VKT: first, ride-hailing significantly reduces or eliminates altogether the time and distance traveled in search of parking, a relevant issue as this *cruising for parking* behavior is a major contributor to congestion in several cities (Shoup, 2006). Second, when someone owns a car, they pay a high fixed cost of capital (acquisition of the vehicle), relative to which the marginal cost for the use of the vehicle is very low. Therefore, some people will tend to make more motorized and/or longer trips if they own a car, relative to the trips made by a person who relies on ride-hailing, where the entire transport cost is associated with the trips made and their length. On the other hand, there is a factor that counteracts these two arguments: a car trip is generally door-to-door (except for the cruising for parking phenomenon), while ride-hailing trips include the extra travel made by the driver from somewhere else to the passenger's starting point, plus the passenger-free traffic the car adds at the end of the trip (when it travels to look for another passenger). Then, the net effect of ride-hailing applications on externalities such as congestion, pollution and accidents, compared to the private car, depends on the size of these opposing effects.

Compared to traditional taxis, ride-hailing platforms have the advantage of reducing the number of kilometers that

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/ujst.
[1]On this last issue see Greenwood and Wattal (2015) who provide evidence using data from California that Uber reduces alcohol/DWI homicides. See also Dills and Mulholland (2016). For the case of Chile, see Lagos, Muñoz, and Zulehner (2018).

drivers travel without passengers (Cramer & Krueger, 2016). Finally, in comparison with public transportation, cycling or walking, a substitution toward ride-hailing increases vehicle kilometers on the street, unless the substitution of local bus trips is more than compensated by an increased number of trips that combine ride-hailing with longer rail or express bus services, in replacement of car trips (the so-called "last mile problem").[2] Therefore, taking all these effects into account, it is impossible to predict ex-ante the effect of ride-hailing platforms on transport externalities. What is clear though is that such effects are not constant throughout the day, calling for flexible regulation of these services, including the possibility of introducing a fee on ride-hailing that is related to the number of vehicle kilometers added in different time periods and locations.

There is a small but growing literature on the impact of ride-hailing applications on congestion, with very few studies published in peer-reviewed journals. Henao (2017) cites the reluctance of commercial ride-hailing companies to share meaningful data as one of the reasons behind the scarcity of academic studies on the subject, being an exception the data available in New York. The literature comprises studies based on the following types of data: user surveys (e.g., Alemi, Circella, Handy & Mokhtarian, 2018; Clewlow & Mishra, 2017; Henao & Marshall, 2018; Rayle, Dai, Chan, Cervero, & Shaheen, 2016), actual taxi or ride-hailing data (Nie, 2017; Schaller, 2017) and google searches as a proxy for the use of ride-hailing in cities (Hall, Palsson, & Price, 2018; Li, Hong, & Zhang, 2016).

The lack of data on most cities explains why various authors have not been able to conclusively answer the question of whether ride-hailing applications increase or reduce congestion. For example, a study undertaken for the city of Vancouver (Ngo, 2015) states that there is inconclusive evidence as to whether these applications increase or decrease VKT and thus congestion.

Rayle et al. (2016) also remain neutral as to the impact of these applications on congestion. However, their intercept survey of San Francisco during May and June 2014 indicates that – up to that date – there was no clear evidence that these services had influenced car ownership behavior. Their results also indicate that a small amount of travel has been induced by ride-hailing applications. More troubling was their finding that 33% of users declared that they would have otherwise used bus or rail to make their surveyed ride-hailing trip, evidence that ride-hailing applications are likely increasing traffic externalities such as congestion and air pollution. The total effect on environmental externalities depends on the type of service that is mostly replaced (bus and/or train) and on the fuel type used by cars and transit services, among other factors. Rayle et al. (2016) conclude that more research is required and that the impact of these applications on congestion should consider the "induced travel effect, travel made by drivers without passengers, potential substitution from public transit, and the impact of ridesourcing on users' driving."

In the case of New York, City of New York (2016) finds that ride-hailing services do not appear to be driving the increasing severity of vehicle congestion in the Central Business District (CBD). However, it also recognizes that this may change in the future and the impact will depend on the proportion of passengers that substitute from car-based modes as opposed to public transit.[3] On the other hand, Schaller (2017) estimates a significant increase in VKT in New York (whole city) due to the use of ride-hailing applications, and that most of the growth in ride-hailing use between 2013 and 2016 was outside the CBD. Outside North America, Nie (2017) reports a slight increase in taxi congestion due to the rapid growth of ride-hailing traffic in Shenzhen, China.

A number of opinion pieces on the matter have also being published. For example, Hensher (2017) points out at the potential negative effects of substitution away from mass public transportation, with no quantitative data to measure the size of this effect. He also makes the point that an impact of these applications on car ownership may not reduce congestion, as, in the end, a trip in a small vehicle is an addition of VKT irrespective of who owns the vehicle. However, ride-hailing does have an impact on reducing the demand for parking, as previously discussed, which in turn is an opportunity to relocate parking spaces, for example, to mixed land uses (Henao & Marshall, 2017). A roundtable discussion by OECD/ITF (2016) concluded that ride-hailing applications represent only a small fraction of overall vehicle kilometers and thus it does not make sense to target this policy issue if overall vehicle congestion was not also addressed. However, this may change in the future and OECD/ITF (2016) recognize that addressing the issue of the impact of ride-hailing applications on congestion may be important in certain areas and time periods.

More empirical evidence on the effects of ride-hailing on traffic is provided by Hall et al. (2018), Li et al. (2016), and Clewlow and Mishra (2017). Hall et al. (2018) note that ride-hailing applications can solve the last mile problem, related to access to and from transit services. As such, these two services may be complementary rather that substitute. The authors estimate that, on average, there is an increase in public transportation use thanks to Uber, with heterogeneity noted as Uber reducing public transportation ridership by 5.7% in smaller cities while increasing public transit ridership by 0.8% in the larger cities. Therefore, the predominance of the complementary or substitute nature of the relationship between Uber and public transportation is context dependent. On the other hand, Clewlow and Mishra (2017) report survey results for seven major US cities in which respondents were asked whether they used more or less transit services since the take-up of ride-hailing applications. For buses, 6% more respondents said they use less of this service compared to those that said they use it more. The equivalent figure for light rail is 3%. On the other

[2]An optimization approach to integrate ride-hailing with public transportation is introduced and applied by Chen and Nie (2017).

[3]City of New York (2016) does recognize that ridesourcing applications have eroded an important source of transit funding (special levy on taxi rides) in spite of the fact that ridesourcing trips are subject to an 8.875% sales tax, 0.375% of which go directly to the Metropolitan Transit Authority.

hand, for commuter rail 3% more respondents said they use more of this service compared to those that said they use it less.[4] The potential of ride-hailing to integrate with mass transit is further discussed at length by Iacobucci, Hovenkotter, and Anbinder (2017) and Dinning and Weisenberger (2017).

Li et al. (2016) use a difference in difference estimator approach on annual traffic data of US urban areas. They find that the appearance of Uber is associated with a reduction in traffic congestion at a metropolitan scale. As an underlying explanation, they conjecture that ride-hailing applications such as Uber have the potential to reduce car ownership, increase car occupancy rates due to ride sharing and delay trips during peak hours (due to surge pricing). However, the separate effect of the standard Uber and Uberpool (the carpooling alternative that exist in some cities) could not be disentangled[5] and the results do not preclude the possibility that in some periods and areas within cities (peak times in financial or commercial districts) ride-hailing use may indeed increase congestion.

Clewlow and Mishra (2017) conjecture that ride-hailing has most likely increased VKT in major American cities, as they find that between 49% and 61% of ride-hailing trips would not have been made at all or would have been made by walking, cycling or public transportation. However, the authors recognize that net VKT changes are unknown. They also correctly note that to quantify this impact one must know the mode ride-hailing applications are substituting from (driving, transit, walking, and cycling), the number of passenger kilometers in ride-hailing trips, and the additional kilometers traveled without passengers by cars linked to these applications. These effects are considered in this paper as discussed further below. Henao and Marshall (2018) estimates a notorious increase of 84% in VKT due to ride-hailing in Denver, Colorado, based on 311 ride-hailing trips driven and surveyed by the author himself. In a similar vein, Lewis and MacKenzie (2017) analyze through a survey the impact of UberHOP, a fixed-route commute-focused Uber application, when tested in Seattle in 2016 and find that UberHOP riders predominantly replaced transit rides rather than personal vehicles.

The link between ride-hailing applications and congestion is not only an academic matter. It has important policy implications for authorities working to develop public incentives for more sustainable urban mobility patterns. Several cities, including Seattle, Chicago, and Portland in the US and Mexico City, charge special levies on ride-hailing application services to finance special accessibility or mobility funds (Ngo, 2015). Schaller (2017) also highlights the need of a public policy response that takes into account the increased use of ride-hailing in New York. More interesting, there is a growing tendency to link these charges to congestion. This is the case of Sao Paulo, Brazil, where the municipal authorities recently introduced a charge to ride-hailing based services according to the number of kilometers traveled. The stated purpose of the municipal authorities is to differentiate this charge according to the congestion caused by zone and time of day. Thus, a deeper and more precise understanding of the link between ride-hailing applications and congestion will be paramount to guide these new regulatory frameworks worldwide.[6]

The aim of the present paper is to expand the nascent literature on the effect of ride-hailing applications on travel behavior and traffic externalities along two lines. First, we present a multimodal model to analyze the different parameters that determine the impact of these new application-based services on VKT. The literature has discussed several different channels whereby these services can affect total VKT, such as the passenger occupancy rates among alternative transport modes, substitution from high occupancy modes such as public transportation, induced travel, vehicle kilometers in taxi and ride-hailing services without passengers, the impact of private vehicles searching for parking, among others. We hope to clearly spell out how each of these factors interacts to determine the overall impact on VKT.

Second, we parameterize this model using the information gathered from an online survey regarding travel patterns and use of Uber in Chile. There were 1600 respondents, 91% of which were from Santiago. Although this was a voluntary response survey and therefore the sample is not random and potential biases may be present, further below we contrast the data with the 2012 Origin Destination Survey for Santiago. Furthermore, in the simulation approach used in this paper we introduce ways to tackle potential biases. Our sample is much larger than the interception survey of Rayle et al. (2016) and it covers all time periods.[7] The survey in-itself reveals interesting information regarding the motivation and evaluation of Uber by Chilean users, and that ride-hailing has different effects on travel behavior at day and night. And to our knowledge it is the first-time information of this kind is presented from a country or city outside the United States.

We use the survey results from Santiago to parameterize the model. However, some parameters are not covered by the survey and are borrowed from the literature. Since there is uncertainty regarding most parameters, we assume a range of values for each case and undertake a Monte Carlo simulation in order to examine the likely impact of ride-

[4]One cannot infer the change in patronage of transit services from these figures since the change in the number of trips by each respondent are not reported, only whether people use them more or less.

[5]This is a very relevant issue as, for example, A. E. Brown (2018) shows that 32% of Lyft trips at peak periods were on the pooled service Lyft Line in Los Angeles.

[6]As reviewed by Beer, Brakewood, Rahman, and Viscardi (2017), there is a great diversity in the ride-hailing regulatory frameworks applied by cities, including driver-related regulations (such that background checks, vehicle registrations, special driving licences and external vehicle displays) and company-related regulations (e.g., caps on ride-hailing vehicles in specific areas, obligation to share data with the regulator and to provide a list of drivers).

[7]Rayle et al. (2016) obtain 380 completed responses and their interception survey was undertaken during two months on weekdays and Saturday evenings.

hailing applications on VKT in Santiago.[8] Besides providing survey results for a case outside the United States, the model developed in this paper allows for a more detailed understanding of what could be driving the aggregate results of papers such as Li et al. (2016). To the best of our knowledge, this is the first paper that attempts to measure the quantitative impacts of the different effects in the interplay between the advent of ride-hailing platforms and VKT.

The remainder of the paper is organized as follows. The next section presents the model. We then describe the survey and results. Following that we explain how the model was parameterized and we present the Monte Carlo results. The paper ends with a summary of our main conclusions, policy implications and areas for further research.

2. Conceptual analysis of the impact of ride-hailing applications on VKT

We model the effect of ride-hailing on the number of VKT by different transport modes, as the most common traffic externalities -like congestion, pollution and accidents- are directly related to VKT. We define V_a as the number of trips in private car use, V_{app} as the number of trips in ride-hailing services, V_t as the number of trips in taxis, and V_b as the number of trips in bus.[9]

There are certain specificities of each mode that must be taken into account in order to transform trips into vehicle kilometers. For the private car mode, the number of VKT will have to consider the length of the average trip (L_a) and the average occupancy rate in this mode (O_a). In addition, private cars also congest the roads when looking for a parking space (e.g., Arnott & Inci, 2006; Shoup, 2006). We take this effect into account by using a multiplier ($\theta > 0$) on the average car trip length. Thus, total vehicle kilometers in the car mode will be:

$$VK_a = (1+\theta)\cdot L_a \cdot \frac{V_a}{O_a} \tag{1}$$

where the number of cars traveling is V_a/O_a. The analogous relationship for taxi vehicle kilometers is:

$$VK_t = (1+\mu_t)\cdot L_t \cdot \frac{V_t}{O_t} \tag{2}$$

where μ_t is a parameter that accounts for kilometers traveled empty while looking for passengers (as a proportion of kilometers traveled with passengers on board) and O_t is the average occupancy rate of taxis (excluding the driver).

Bus vehicle kilometers is given by:

$$VK_b = \beta \cdot L_b \cdot \frac{V_b}{O_b} \tag{3}$$

where β is an equivalence factor between buses and light vehicles. This parameter will be >1 and reflects the fact that one bus will use the space equivalent to several cars, depending on its size (for example, 1 bus = 2 pcu – passenger car units).

Vehicle kilometers using a ride-hailing application are given by:

$$VK_{app} = \left(1+\mu_{app}\right)\cdot L_{app} \cdot \frac{V_{app}}{O_{app}} \tag{4}$$

where μ_{app} is – as in the case of taxis – a parameter that considers that vehicles will circulate without passengers some extent. We expect this parameter to be lower than in the case of taxis (i.e., $\mu_{app} < \mu_t$), owing to the use of an application to find customers rather than cruising the streets looking for them, and to GPS-based shortest path routing.[10]

An average trip has an origin-destination shortest path distance $\overline{L}$. However, the actual number of kilometers traveled between the origin and destination will differ between each mode. For example, in a bus, it is probable that the trip will be longer since buses run on fixed routes and these will probably not coincide exactly with the shortest path between the origin and destination of the trip.[11] Therefore, the number of kilometers traveled by bus will be:

$$L_b = (1+\tau_b)\cdot \overline{L} \tag{5}$$

where τ_b is a parameter reflecting the extra vehicle kilometers in bus trips above the shortest path of the trip. Equation (5) only includes motorized travel distance for the computation of VKT, that is, walking to and from bus stops is not included.

Likewise, for private car travel, since users pay a fixed cost rather than a variable charge per kilometer and that not all drivers have GPS or similar devices for routing, it may be that trip length is longer. Therefore, the trip length is:

$$L_a = (1+\tau_a)\cdot \overline{L} \tag{6}$$

In the case of taxis, since in general they do not all use GPS systems, at least in Santiago, we also expect trip length to be somewhat higher than the shortest distance between origin and destination:

$$L_t = (1+\tau_t)\cdot \overline{L} \tag{7}$$

For ride-hailing services we assume that they take the shortest route possible and assume it is equal to $\overline{L}$.

With these assumptions, the total number of VKT will be:

$$VK_{tot} = VK_{app} + VK_t + VK_p + VK_b \tag{8}$$

or,

$$VK_{tot} = \overline{L}\cdot\left[\frac{\left(1+\mu_{app}\right)\cdot V_{app}}{O_{app}} + \frac{(1+\mu_t)\cdot(1+\tau_t)\cdot V_t}{O_t} + \frac{(1+\theta)\cdot(1+\tau_a)\cdot V_a}{O_a} + \beta\cdot\frac{(1+\tau_b)\cdot V_b}{O_b}\right] \tag{9}$$

[8] OECD/ITF (2015) also use scenarios or simulations to study the effects of shared self-driving cars on several variables of interest, including VKT, in an application for Lisbon, Portugal.

[9] We assume that other modes such as cycling or walking do not cause congestion.

[10] As traditional taxis also incorporate smartphone-based e-hailing applications to contact costumers, as it is occurring in many cities (e.g., the app Easy Taxi in Chile), these two parameters will tend to converge.

[11] However, this may imply more walking to and from bus stops rather that an increase in the number of vehicle kilometers.

Table 1. Survey responses by city residence.

City of residence	Observations	Percentage (%)
Santiago	1458	91
Greater Valparaiso	58	4
Greater Concepción	45	3
Other	39	2
Total	1600	100

Taking the derivative of Expression (9) with respect to the number of ride-hailing trips, V_{app}, will indicate how total vehicle kilometers change when ride-hailing applications increase ridership, at the expense of other modes:

$$\frac{dVK_{tot}}{dV_{app}} = \underbrace{\overline{L} \cdot \frac{(1+\mu_{app})}{O_{app}}}_{\text{ride-hailing effect}} + \underbrace{\overline{L} \cdot \frac{(1+\mu_t)\cdot(1+\tau_t)}{O_t} \cdot \frac{dV_t}{dV_{app}}}_{\text{taxi effect}} + \underbrace{\overline{L} \cdot \frac{(1+\theta)\cdot(1+\tau_a)}{O_a} \cdot \frac{dV_a}{dV_{app}}}_{\text{car effect}} + \underbrace{\overline{L} \cdot \beta \cdot \frac{(1+\tau_b)}{O_b} \cdot \frac{dV_b}{dV_{app}}}_{\text{bus effect}} \tag{10}$$

Equation (10) can be interpreted as the change in total VKT due to the addition of one extra trip by ride-hailing. On the one hand, there is an increase in VKT given by the average number of vehicle kilometers added by the ride-hailing vehicle used in the trip, which is named as "ride-hailing effect" (the first term of the right-hand side). This direct increase in VKT is counterbalanced with a reduction in the expected number of kilometers in the competing modes taxi, private car, and bus. These taxi, car and bus effects are equal to the average number of kilometers that a single trip on these modes add to the streets, times the substitution rates $\frac{dV_t}{dV_{app}}$, $\frac{dV_a}{dV_{app}}$ and $\frac{dV_b}{dV_{app}}$ between trips in ride-hailing applications and trips in taxi, car and bus, respectively.

The modal substitution rates in Equation (10) are expected to be negative, because the increase in VKT by ride-hailing will come from a reduction in VKT by other road modes. Moreover, the absolute value of the summation of these three substitution rates is <1;

$$\left| \frac{dV_t}{dV_{app}} + \frac{dV_a}{dV_{app}} + \frac{dV_b}{dV_{app}} \right| < 1 \tag{11}$$

because some trips in ride-hailing applications are new trips or come from modes that do not increase VKT, like metro (subway), walking and cycling. The fact that a combined ride-hailing-subway trip may replace a trip previously made fully by private car (therefore increasing metro ridership and reducing VKT) is numerically included in a scenario of Section 4.

Thus, the last three terms of the right-hand side of Equation (10) will be negative while the first term is positive. If Expression (10) is positive, ride-hailing applications increase total VKT. Likewise, if Expression (10) is negative, ride-hailing applications decrease VKT. Average trip lengths and occupancy rates of all modes play a key role in the final outcome.

In deriving Equation (10), we assume that several parameters of Equation (9) are constant and do not change with the increase in ride-hailing trips. This is the case of the equivalence factor between buses and light vehicles (β) which should not be expected to change with a re-distribution of rides among modes. The parameters that account for extra kilometers above the shortest route for each mode (τ_t, τ_a, and τ_b) could in principle change, particularly for the case of buses, if the trips that switch to ride-hailing are disproportionally those where existing routes are poorly aligned with the trip's origin and destination. However, even in this case, unless the change in bus ridership leads to significant re-routing of bus routes one would not expect a change in this parameter.

Finally, the deadhead kilometers for taxis and ride-hailing applications (μ_{app} and μ_t) and the average occupancy rates of each mode (O_j) are also assumed constant in deriving Equation (10). This is justified by the assumption that there are supply changes in each mode as customers substitute trips towards ride-hailing applications, in a way that average occupancy rates and deadhead kilometers remain constant. Thus, it is a medium-run evaluation of the impacts of ride-hailing applications on vehicle kilometers. In the short-run, if the same number of taxis and buses are circulating (and only private car kilometers are saved by ride-hailing use), then the probability that ride-hailing applications increase VKT is much higher than what Equation (10) would predict.

3. Input data

In this section we describe the data used to parameterize the model. We first present the survey results and then discuss other parameters taken from the literature.

3.1 Uber use survey

An online survey to understand patterns of Uber use in Chile was undertaken between 11th and 20th January 2017. The questionnaire was made in Google Forms and was distributed online through email lists and internet forums from Universidad de Chile and through social media (Twitter, Facebook). A snowball sample was created as respondents were encouraged to share the survey with other people. It was addressed to Uber users, this being the first and most widely used ride-hailing application in Chile, although results are extensible to other ride-hailing applications. In total, there were 1600 completed surveys, 91% of which were from people residing in Santiago (Table 1). This is expected since Uber was first introduced in the capital and Santiago is by far Chile's most populated city.

Table 2. Descriptive Statistics of the survey compared to the Santiago 2012 Origin Destination Trip survey.

	Uber survey (Santiago)		Overall 2012 ODS		Taxi users 2012 ODS	
Age	*N*	%	*N*	%	*N*	%
Less than 20	46	3.1	4054	7.7	45	2.7
Between 20 and 35	1070	72.6	15,203	28.8	320	19.4
Between 36 and 50	281	19.1	11,870	22.5	425	25.8
Between 51 and 65	61	4.1	11,630	22.1	347	21.1
Over 65	16	1.1	9988	18.9	509	30.9
	1474		52,745		1646	
Gender						
Male	851	57.7	28,375	47.2	659	36.9
Female	623	42.3	31,679	52.8	1128	63.1
	1474		60,054		1787	
Monthly Income (US $)						
No response	14	0.9	1977	5.7	58	4.5
Less than $312	331	22.5	7333	21.3	275	21.4
$312 to $624	129	8.8	13,284	38.5	397	30.9
$625 to $937	101	6.9	6377	18.5	217	16.9
$938 to $1,562	214	14.5	3587	10.4	180	14.0
$1,563 to $3,125	393	26.7	1557	4.5	128	10.0
Over $3,125	292	19.8	366	1.1	29	2.3
	1474		34,481		1284	
Family car ownership						
0	408	27.7	11,074	60.6	1181	66.1
1	625	42.4	5787	31.7	473	26.5
2 or more	441	29.9	1403	7.7	133	7.4
	1474		18,264		1787	

Source: Own elaboration from Santiago's Origin Destination Survey (ODS; SECTRA, 2014). Income from the 2012 ODS was inflated using the change in the Consumer Price Index between July 2012 and July 2017. Original income was presented in Chilean Pesos (CLP). The exchange rate at the time of writing this was CLP 640 per USD. Observations reporting zero monthly income were excluded. The 2012 ODS frequency weights were not used. However, the change in the frequencies are small if these weights are used to tabulate the data. Only persons over 15 years of age were considered in the age frequency data for the 2012 ODS. Taxi users in the 2012 ODS include those that use taxi in one of the stages of multimodal trip.

Table 2 presents descriptive statistics of the responses and compares them to information from the 2012 Origin Destination Survey (ODS) of Santiago[12] (Muñoz, Thomas, Navarrete, & Contreras, 2015; SECTRA, 2014), both overall and among taxi users. In order to make the comparison meaningful only survey observations from Santiago are used.

From Table 2 we can see that survey respondents were overwhelmingly young, over 75% less than 36 years old. This does not reflect the overall age composition of the 2012 ODS for Santiago. Even if only people taking taxi trips are considered, the age distribution is very different. Among taxi users in the 2012 ODS over 50% are 51 years or older. This age composition, if it were representative of Uber users, mirrors findings from the Unites States (Alemi et al., 2018, Rayle et al., 2016, Clewlow and Mishra, 2017), where ride-hailing apps are mainly used by younger people with higher income than the average population. In our case, age composition may also be influenced by the sampling method, as younger people are more familiar with modern digital technology and they are also more likely to use social media and thus answer our survey. A face-to-face survey on ride-hailing use delivered across Santiago by Chile's National Productivity Commission also found that the largest rate of ride-hailing users are younger people, between 18 and 29 years old, but this group only accounted for 30.1% of survey respondents (CNP, 2018). The fact that the sampling method in our survey over-represents young users is accounted for in a scenario in Section 4.

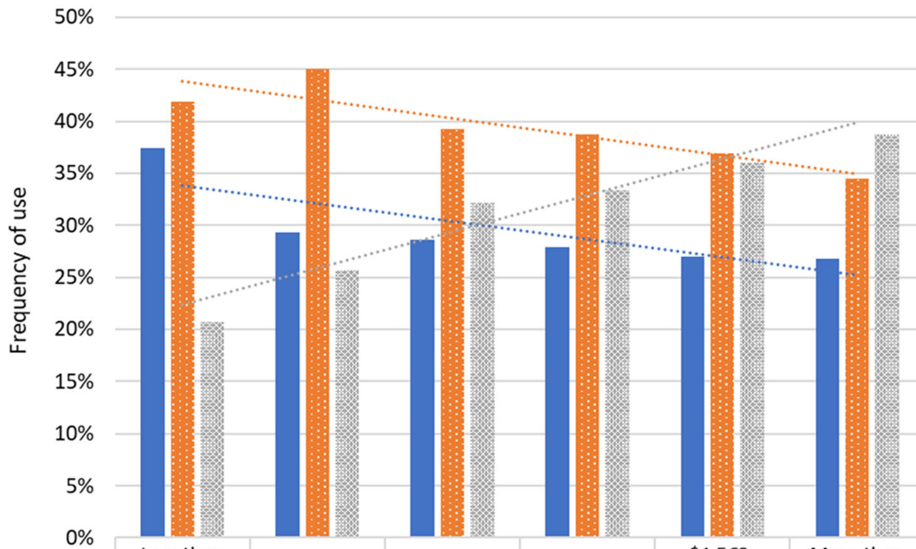
[12]In Santiago, origin destination surveys that cover the whole metropolitan area have been conducted by the government every 10 years.

Our survey results also indicate a higher response among male users while the 2012 ODS is more balanced gender wise. It is interesting to note that females are more intense taxi users compared to males (63%–37%), perhaps due to security concerns in other transport modes.

Our survey responses are also more skewed towards higher income individuals and from households that tend to own cars. Over 70% of respondents come from households with at least one car, while less than 40% of households own cars among the general population and even less among taxi users. Once again, we cannot be sure whether these differences are due to the differing composition of Uber users in Santiago or whether it is due to the response rate to our survey. As mentioned above, we conjecture that there is a bit of both.

The survey included three categories for the intensity of Uber use. Low frequency users were those that claimed to "use it very few times overall." Medium frequency users are those that said to "use it very few times per month," while high frequency users where those that claimed to "use it every week, almost every day or every day".

Figure 1 shows the intensity of use by income groups. It can be seen that the intensity of use increases with income. This may be due to the larger cost of an Uber trip relative to the public transport fare in Santiago (around 1 US dollar), lower access to smartphones with an active data account among lower income households and probably because in Chile lower income individuals do not have access to credit cards (although in 2016 Uber started to accept cash for their service). However, it is striking that there are many lower and middle-income individuals (relative to the survey sample) that are high or medium intensive users of this application; it is expected that tertiary education students are in this group.



	Less than $312	$312-$624	$625-$937	$938-$1,562	$1,563-$3,125	More than $3,125
Low	37%	29%	29%	28%	27%	27%
Medium	42%	45%	39%	39%	37%	34%
High	21%	26%	32%	33%	36%	39%

Monthly income

Figure 1. Frequency of ride-hailing use versus personal income.

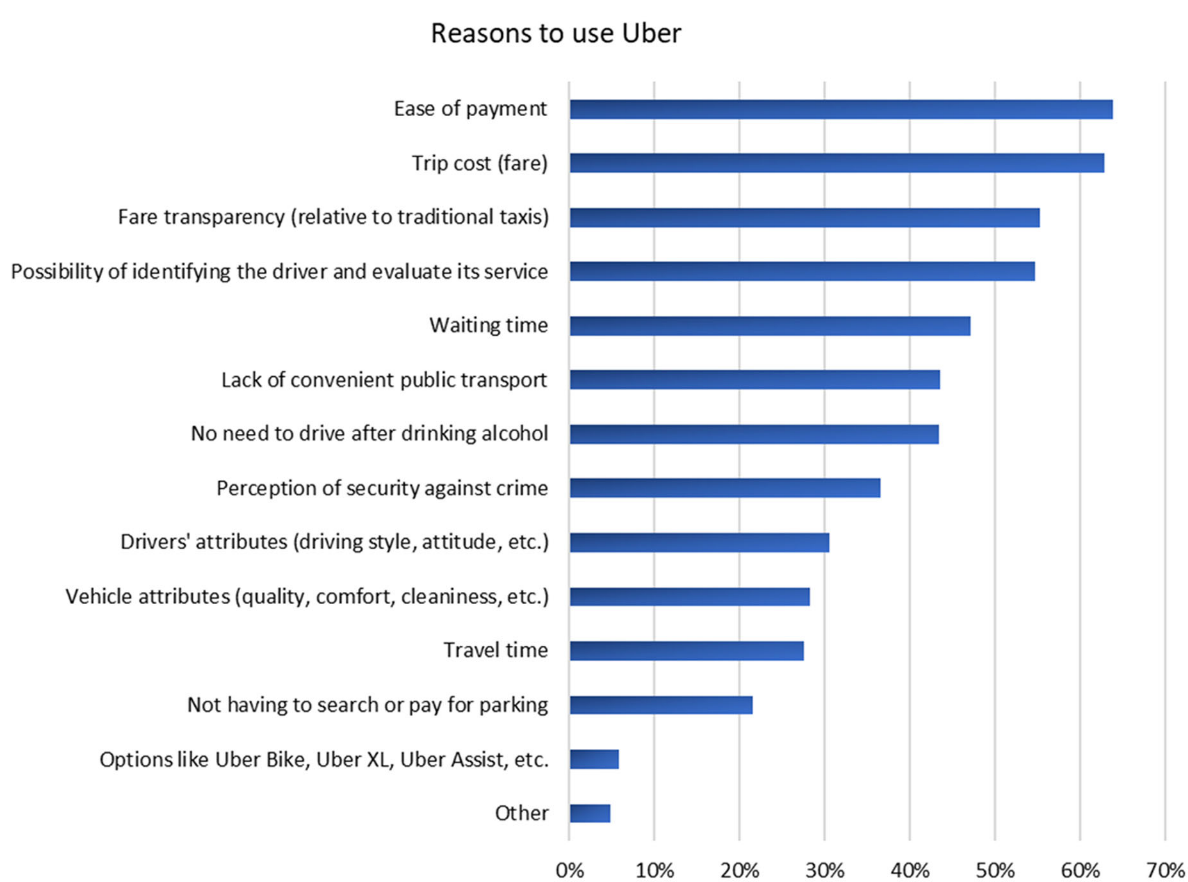


Figure 2. Respondents' reasons to use Uber ("When you travel using Uber, what are the reasons for using it? you can choose more than one").

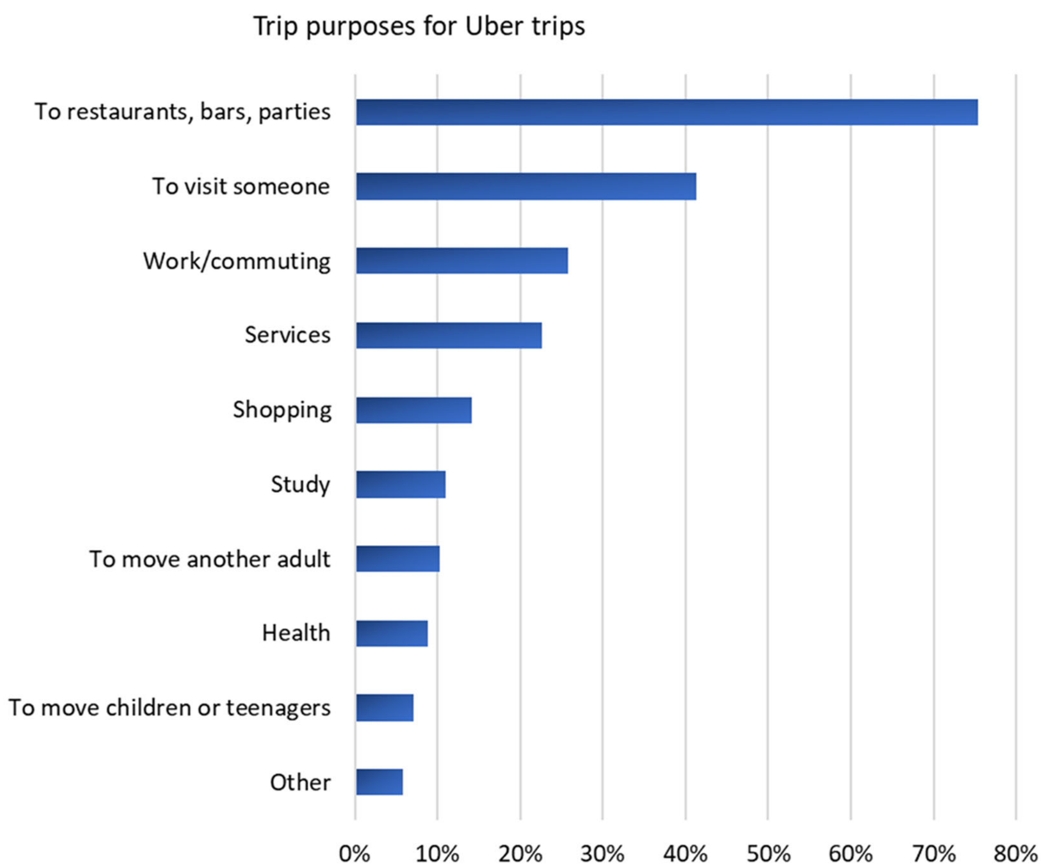


Figure 3. Purpose of trips made by Uber ("For which type of trips do you use Uber? you can choose more than one").

Figure 2 shows the answers to the question "What are your reasons to use Uber?" in which respondents could answer more than one alternative. The most important reasons for using Uber are the ease of payment,[13] trip cost, the transparency of the charging system compared to taximeters, and the possibility of identifying the driver and rating his/her performance. Other important motives include short waiting times, lack of convenient public transportation, not having to drive after drinking alcohol and the perception of the service being more secure than other modes.

The next question is about trip purposes for which respondents use Uber. Figure 3 depicts that more than 70% of respondents use Uber for social and recreational purposes like going to bars, restaurants and parties, while Uber is used by less than 30% of respondents for compulsory activities, like trips to work or study (respondents were able to select all trip purposes for which they use Uber, so total exceeds 100%). This finding is in line with the actual timing of Uber trips in Santiago, as the weekly peak of Uber use is on Fridays and Saturdays between 9 PM and 12 AM, according to detailed trip timing information given by Uber to a local newspaper.[14] This period is the usual time in which people go out on weekends in Santiago.

[13]Ease of payment was also the number one reason to use ridesourcing apps in the San Francisco survey reported by Rayle et al. (2016).

[14]"Uber detecta mayor aumento de viajes entre zonas periféricas y el centro en horas punta", El Mercurio newspaper, March 4th, 2017, http://impresa.elmercurio.com/Pages/NewsDetail.aspx?dt=2017-03-04&dtB=04-03-2017%200:00:00&PageId =9&bodyid =3, accessed October 17th, 2017.

The questionnaire also asked for the last trip made using Uber. In Santiago, there were 1,474 responses. Regarding trip length of the last trip made, 58% of trips are shorter than 6 km and 84% are shorter than 10 km, as reported by users.

One of the key parameters for our model is the transport mode that would have been used in the counterfactual scenario that Uber was unavailable. In total, close to 41% of users say they would have taken a traditional taxi in their last trip (Figure 4). Thus, this application is clearly a substitute for traditional cab services, however, the majority of trips seem to come from other modes. What looks more problematic in terms of VKT effects is that 32.5% of users said they would have taken public transportation and only 12.1% would have taken an automobile. Walking and cycling do not seem to have a high substitution rate with Uber. By way of comparison, with a survey using a representative sampling method, Tirachini and del Río (2018) report that 39.2% of survey respondents replaced taxi trips with ride-hailing, 37.6% replaced mass public transport (bus and/or metro), 15.9% replaced car trips and 12.9% replaced *colectivos* (shared taxis running on fixed routes).[15] Therefore, our results may be considered conservative regarding the effect of modal substitution towards ride-hailing for the analysis of VKT changes.

[15]In this survey, respondents could mention more than one mode as being replaced by the use of ride-hailing.

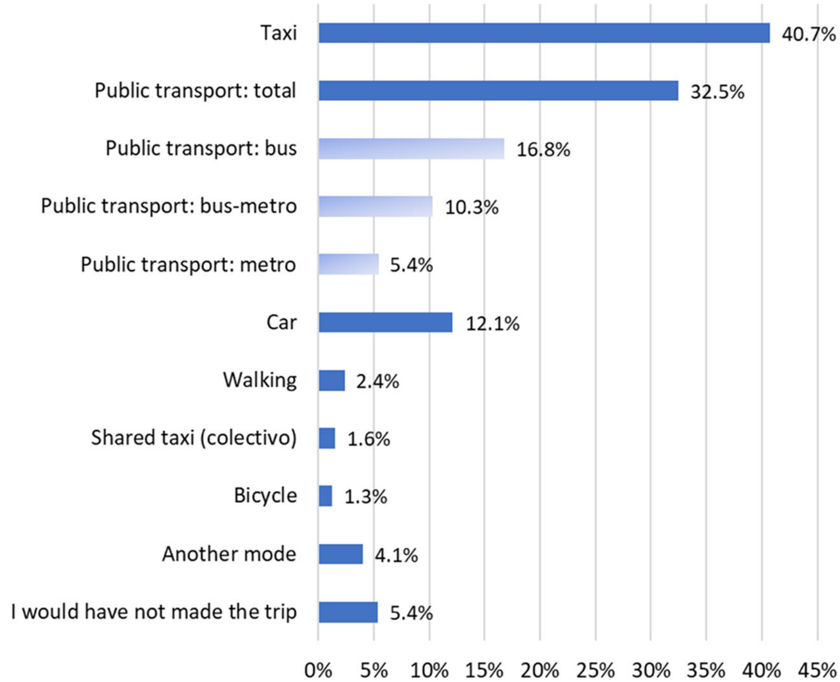


Figure 4. Ride-hailing modal substitution ("For your last Uber trip, if Uber did not exist, how would you have made that trip?").

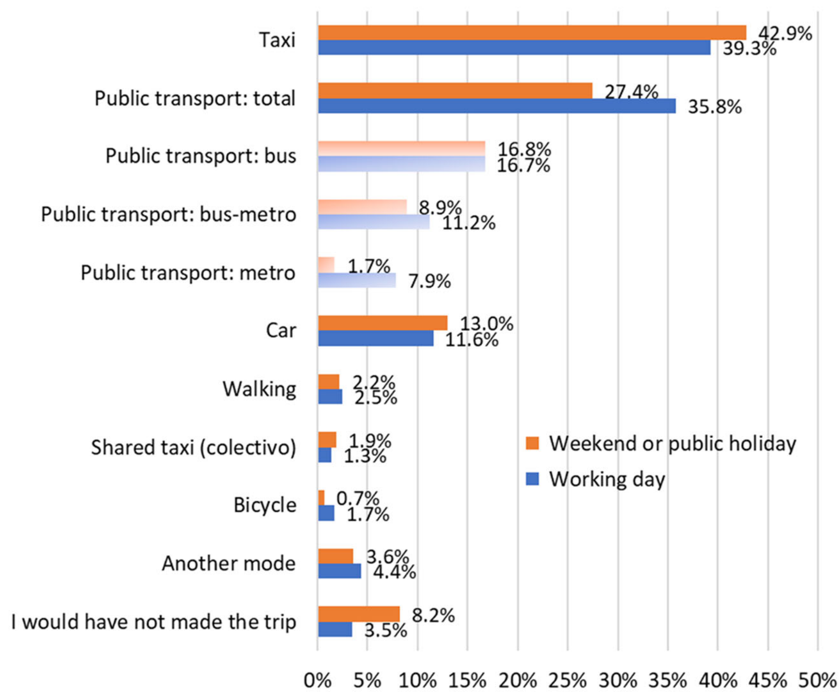


Figure 5. Ride-hailing modal substitution by type of day ("For your last Uber trip, if Uber did not exist, how would you have made that trip?").

When we analyze the substitute mode for the last trip made during weekdays and weekends or holidays (Figure 5) we see that 35.8% of Uber users would have used public transportation during a weekday trip. This is of some concern given that it was shown above that most Uber trips during weekdays are taken during or very close to congested rush hour times (7 AM to 9 AM and 6 PM to 8 PM are the rush hour times in Santiago).

The latest household travel survey delivered in Santiago shows that in a normal working day 25.7% of trips are made by car, 25.0% are made by mass public transportation, 34.5% by walking, 4.0% by bicycle and 1.7% by taxi (SECTRA, 2014). Therefore, Uber is disproportionately replacing more public transportation and specially taxi trips, as compared to the replacement of car trips.

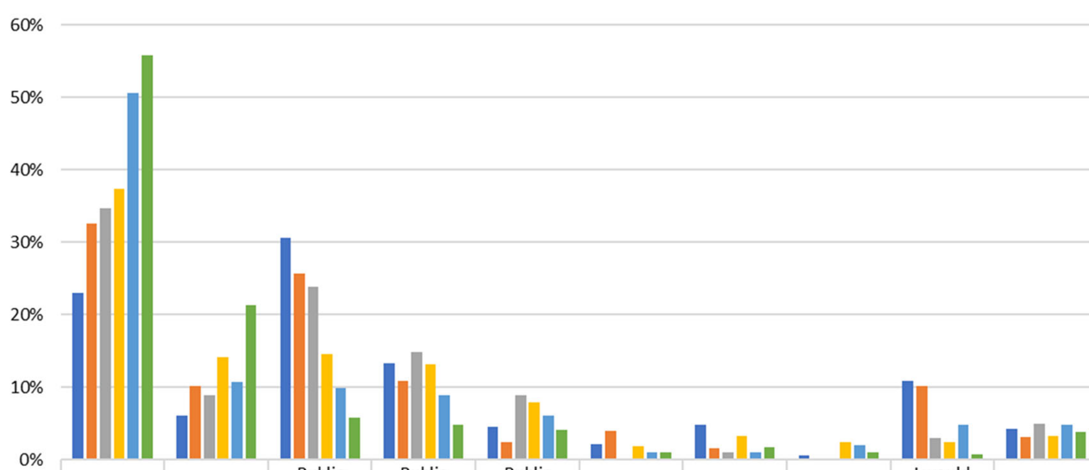
If we look in more detail to Uber trips taken during weekdays (891 observations) we see that during peak times more than 50% of Uber trips would have been taken otherwise using public transportation, bicycle, walking or using a shared taxi (see Table 3). This points to a potential impact

Table 3. Ride-hailing substitution by time of day – weekdays ("For your last Uber trip, if Uber did not exist, how would you have made that trip?").

Mode	Day – peak		Day – off peak		Night 1 (8 PM to 12 PM)		Night 2 (12 PM to 6 AM)		Total	
Taxi	36%		42%		39%		38%		39%	
Car	11%		11%		12%		13%		12%	
Public transportation: bus	42%	17%	35%	12%	35%	19%	27%	24%	36%	17%
Public transportation: bus-metro		17%		14%		8%		2%		11%
Public transportation: metro		9%		9%		8%		2%		8%
Shared taxi (*colectivo*)	1%		2%		1%		2%		1%	
Bicycle	4%		0%		3%		1%		2%	
Walking	3%		3%		0%		2%		2%	
I would have not traveled	1%		1%		5%		12%		3%	
Another mode	2%		5%		5%		5%		4%	
Total	100%		100%		100%		100%		100%	
Number of observations	224		323		216		128		891	

Table 4. Ride-hailing substitution by time of day – weekends and public holidays ("For your last Uber trip, if Uber did not exist, how would you have made that trip?").

Mode	Day		Night 1		Night 2		Total	
Taxi	39%		42%		47%		44%	
Car	10%		21%		10%		13%	
Public transportation: bus	42%	20%	29%	14%	20%	17%	28%	17%
Public transportation: bus-metro		20%		11%		2%		9%
Public transportation: metro		2%		3%		1%		2%
Shared taxi (*colectivo*)	2%		1%		3%		2%	
Bicycle	1%		1%		0%		1%	
Walking	2%		3%		2%		2%	
I would have not traveled	2%		4%		14%		8%	
Another mode	1%		0%		4%		2%	
Total	100%		100%		100%		100%	
Number of observations	139		157		278		574	



	Taxi	Car	Public transport: bus	Public transport: bus-metro	Public transport: metro	Shared taxi (colectivo)	Bicycle	Walking	I would have not traveled	Another mode
Less than $312	23%	6%	31%	13%	5%	2%	5%	1%	11%	4%
$312-$624	33%	10%	26%	11%	2%	4%	2%	0%	10%	3%
$625-$937	35%	9%	24%	15%	9%	0%	1%	0%	3%	5%
$938-$1,562	37%	14%	14%	13%	8%	2%	3%	2%	2%	3%
$1,563-$3,125	51%	11%	10%	9%	6%	1%	1%	2%	5%	5%
More than $3,125	56%	21%	6%	5%	4%	1%	2%	1%	1%	4%

Figure 6. Ride-hailing substitution versus personal income ("For your last Uber trip, if Uber did not exist, how would you have made that trip?").

on negative externalities such as congestion, pollution and accidents of the introduction of ride-hailing platforms such as Uber. Further below we will use this information to simulate the potential effects of ride-hailing on VKT.

Table 4 presents the same information as Table 3 for weekend and holiday trips (574 observations). Once again over 50% of trips come from modes different from traditional taxis, a result that is consistent with the findings of Rayle et al. (2016).

Figure 6 disaggregate the alternative mode of travel by income level. As expected higher income households substitute more from taxi and private car use while lower income

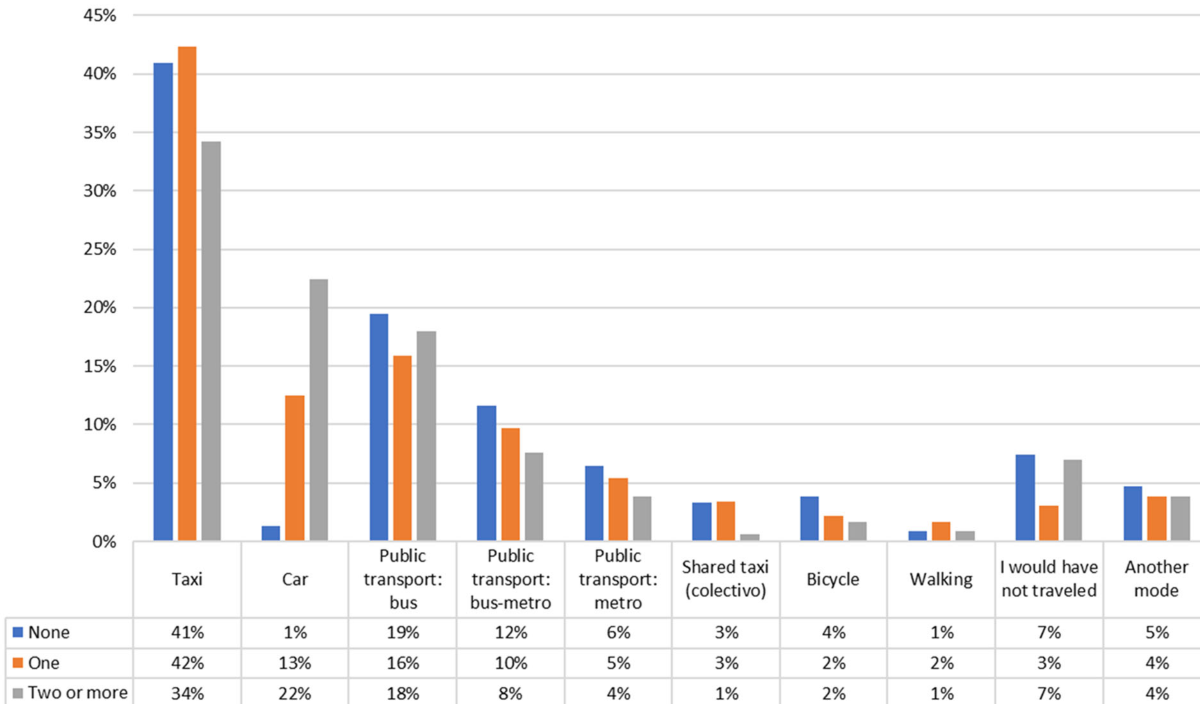


Figure 7. Ride-hailing substitution versus car ownership ("For your last Uber trip, if Uber did not exist, how would you have made that trip?").

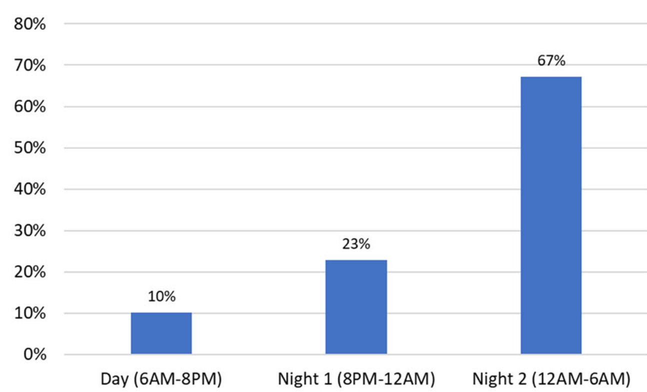


Figure 8. Induced ride-hailing trips by time period.

Table 5. Input parameters, base case.

Parameter	Unit	Min	Max
Trip length $\bar{L}$	km	4.0	8.0
Occupancy taxi O_t	pax/veh	1.3	1.4
Occupancy car O_a	pax/veh	1.4	1.5
Occupancy bus O_b	pax/veh	28	66
Extra distance rate auto τ_a	–	0.0	0.1
Extra distance rate taxi τ_t	–	0.0	0.1
Extra distance rate bus τ_b	–	0.1	0.3
Increased occupancy rate ride-hailing F_o	–	1.0	1.3
Extra distance rate parking θ	–	0.01	0.1
Reduced rate of empty kilometers G_o	–	0.60	0.74
Rate of taxi empty kilometers μ_t	–	0.45	0.58
Bus equivalency factor β	bus/car	1.5	3.0
Substitution rate car	–	−0.09	−0.15
Substitution rate taxi	–	−0.31	−0.51
Substitution rate bus	–	−0.20	−0.34

households substitute more from public transportation. Figure 7 shows that car ownership does not affect much the substitute mode except of course as concerns the alternative use of a private car.

In the survey, 79 respondents (5.4% of the total) said that without Uber they would have not made the trip. It is worth analyzing the time of day of those trips induced by Uber. Results in Figure 8 show that 90% of these trips were made at night, with a majority of them being made late at night (from midnight to 6 AM). Moreover, Figure 6 shows that most of these new trips come from lower income users. Therefore, ride-hailing apps are allowing the engagement in activities that otherwise would have not been undertaken (or not for the desired duration), especially late at night and for lower income users, which are more dependent on public transport that is scarce at night (the Metro service closes before midnight in Santiago).

4. Monte Carlo simulation

4.1. Input parameters

Monte Carlo is a simulation technique that uses randomly generated numbers to simulate processes subject to uncertainty. In this work, we perform Monte Carlo simulations to estimate whether Expression (10) is positive or negative for a wide range of parameter values, that is, if there is an increase or reduction in total VKT due to the addition of ride-hailing trips. A simulation method seems appropriate given the elements that introduce uncertainty on the value of the parameters of Expression (10), including the substitution of other modes by ride-hailing, which is based on the results of the survey described in Section 3.

In the absence of known probability distributions for the random parameters, we apply a simple approach in which random parameters are assumed to follow a uniform distribution on an interval $[a, b]$, where a and b need to be estimated from available data. These input parameters are summarized in Table 5 and explained next.

First, regarding occupancy rates, in SECTRA (2013) the occupancy rate of vehicles was measured in 406 spots across Santiago. Taking the average for all observations, results show that public buses carry between 28 and 65 passengers, that car occupancy rate is between 1.4 and 1.5 passengers per vehicle, and that, when used, taxi occupancy rate is between 1.3 and 1.4 (without counting the driver). However, taxis were running with no passengers between 45% and 58% of the observations.

The large number of times in which taxis run empty of passengers is in the order of estimations made in other cities. The time taxis move without passengers as a rate of the total driving time has been estimated as 41.6% for Berlin (Bischoff, Maciejewski, & Sohr, 2015), 40%–50% for Shenzhen[16] (Nie, 2017), 50%–52% for New York (Cramer & Krueger, 2016) and 61%–62% for Seattle (Cramer and Krueger, 2016). With self-collected data in Denver, Henao (2017) estimates that ride-hailing deadheading distance is between 34.6% and 40.8%, depending on whether the distance to travel from/to home at the beginning/end of the work shift is considered. The deadheading time rate is reported to be larger than the deadheading distance rate (Henao, 2017). Cramer and Krueger (2016) also report the distance rate in which taxis and Uber vehicles drive without passengers, the figures are 59.1% and 61.9% (taxi), 35.8% and 44.8% (Uber) for Los Angeles and Seattle, respectively. Therefore, the distance rate traveled without passengers for Uber is between 60% and 74% the distance without passengers for taxis, a measure of the efficiency induced by the matching between supply and demand that is achieved with ride-hailing applications. We will use these parameters in the simulation as follows:

$$\mu_{app} = G_o \mu_t$$

$$O_{app} = F_o O_t$$

Parameter G_o is the ratio between the percentage of empty kilometers by ride-hailing to the percentage of empty kilometers by taxi, we assume $G_0 \in [0.60, 0.74]$ based on Cramer and Krueger (2016). Parameter F_o is the ratio between the mean ride-hailing occupancy and the mean taxi occupancy, it should be larger than 1 because ride-hailing may make it easier for relatives, friends and acquaintances to travel together, we assume $F_0 \in [1.0, 1.3]$.

For the average trip length, we assume $\overline{L} \in [4.0,\ 8.0]$, following the answers to the survey. We further include that average trip length by private car and taxi is up to 10% larger than average trip length by ride-hailing, assuming that all ride-hailing drivers use GPS navigation for optimal routing, but not all car and taxi drivers do so. As bus routes in general deviate from shortest paths, we assume $\tau_b \in [0.1, 0.3]$.

Regarding cruising for parking, there is no study of this issue in Santiago. It is assumed in the simulation that the average distance searching for parking is between 1% and 10% of the average trip length, with which we obtain an average cruising for parking distance of 340 m. Bus equivalency factor goes between 1.5 bus/car (for a 8-m long bus) and 3 bus/car (for a 18-meter articulated bus), which is the range of bus equivalency factors typically used in Chile (MDS-SECTRA, 2013).

Finally, with respect to the substitution rates $\frac{dV_t}{dV_{app}}$, $\frac{dV_p}{dV_{app}}$, and $\frac{dV_b}{dV_{app}}$, for the uniform distribution we assume a symmetrical range around the mean values found in the survey (40.7% for taxi, 27.1% for bus, 12.1% for car), that is 50% wide, that is, if $\frac{dV_i}{dV_{app}} = c$ on the survey, for the simulation we assume $\frac{dV_i}{dV_{app}} \sim U(0.75c, 1.25c)$. This range is such that the absolute value of the summation of the three substitution rates is no larger than 1, as established in Equation (11). Later, a sensitivity analysis is performed over this parameter.

4.2. Base results

We perform a Monte Carlo simulation of Equation (10) with 20,000 replications.[17] Assuming that parameters of Equation 10 follow a uniform distribution with minimum and maximum values as in Table 5, we obtain that in the base case the probability that ride-hailing reduces VKT is zero. That is to say, in none of the 20,000 replications of Equation (10), its value was negative. The ride-hailing effect in Equation (10) is 5.24 km/trip on average, whereas average taxi, car and bus effects are −2.88, −0.56, −0.10 km/trip, respectively (see Equation 10). Therefore, for each new ride-hailing trip, there is an average increase of 1.70 km.[18] To put it differently, on average, an increase of 1000 m driven in ride-hailing is associated with an average reduction of 550 m of taxi driving, 106 m of car driving and 19 m of bus (on car-equivalent driving). In sum, the average reduction of kilometers in car, taxi and bus combined only amounts to 68% of the average addition of VKT by ride-hailing. To estimate a total Uber effect in VKT, the average increase of 1.7 km per trip should be multiplied by the total number of Uber trips (e.g., during a working day), however, actual data on total Uber trips are not available, therefore only the marginal effect per trip can be estimated.

Although we assumed ride-hailing to be more efficient than taxis in two ways (fewer empty kilometers and a larger mean passenger occupancy rate per trip), the result of an increase in VKT is explained by the substitution of trips previously made by public transportation (bus and/or metro), by the addition of new trips (generated demand by ride-hailing) and, to a lesser extent, by the substitution of trips from other modes like walking and cycling.

[16] Nie (2017) also estimates that with the arrival of ride-hailing, the rate of time taxis run without passengers increased to 50%–70% during 2015, due to the reduction on taxi ridership in Shenzhen. Interestingly, taxi ridership has stabilized in the city during 2016.

[17] We used the well-known sample size formula for the estimation of a mean that is normally distributed (see, e.g., Chapter 7 in Roess, Prassas, & McShane, 2011). First, with 10,000 replications a standard deviation of 0.68 km was obtained. Then, for a 95% confidence interval and a desired margin of error of 0.01 km/trip, we obtain a sample size of 18,570 iterations.

[18] This figure is the mean of all 20,000 Monte Carlo draws. If, instead, we estimate the VKT increase for the expected value of all input parameters, the result is 1.67 km.

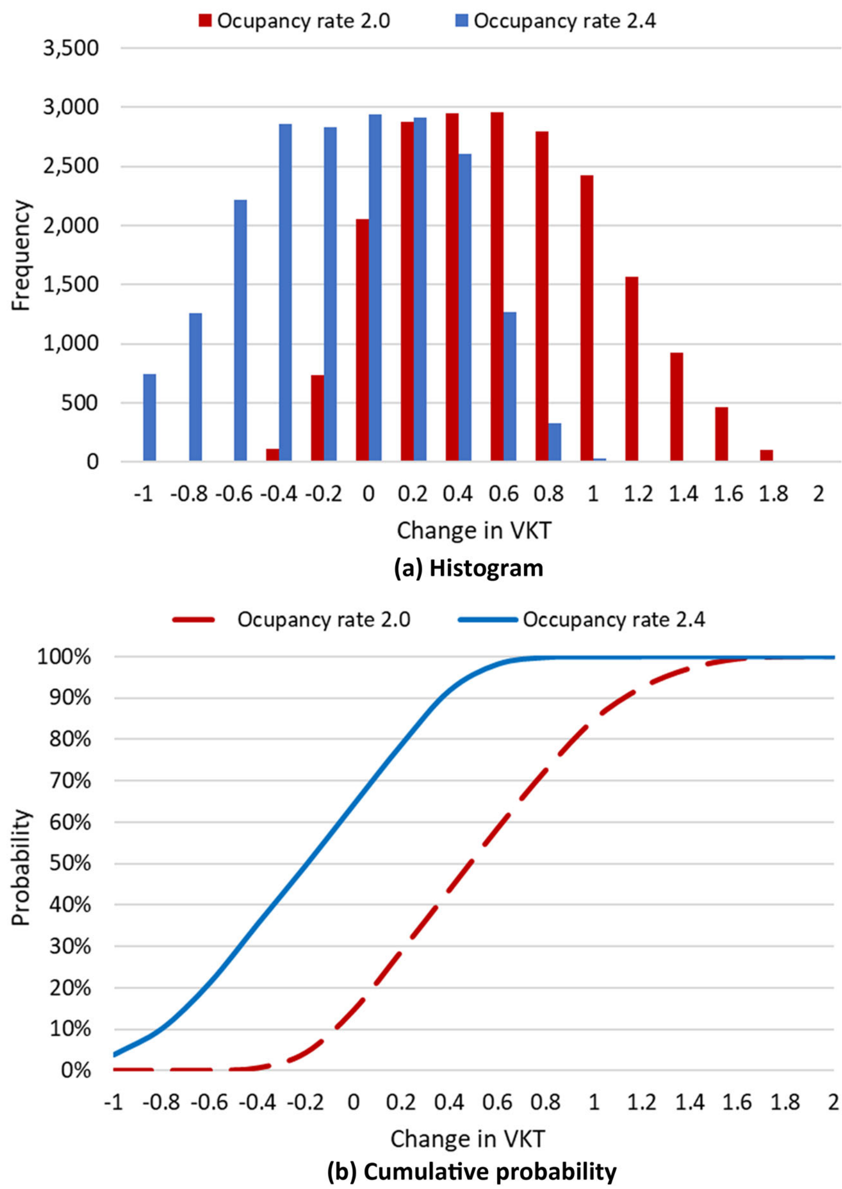


Figure 9. Expected result on VKT for different ride-hailing occupancy rates. VKT, vehicle kilometers traveled.

The finding of an increase of VKT due to ride-hailing is in line with the deterministic analysis of Henao and Marshall (2018) who estimates an increase of 84% in VKT due to ride-hailing in Denver, Colorado. Other authors like Rayle et al. (2016) have not been conclusive on this issue, while Clewlow and Mishra (2017) conclude that ride-hailing has likely increased VKT in the seven cities in which they collected data.

Our result is not sensitive to the assumption on the level of variability of the modal substitution rates around the estimated means. We varied the width of the parameter range from 0% to 50% around the mean for the substitution from taxis, cars and buses, and in all scenarios the result is that all Monte Carlo draws yield an increase on VKT due to ride-hailing. In the next section we perform an analysis of alternative scenarios, by means of introducing new assumptions into specific parameter values of the model.

4.3. Analysis of scenarios

4.3.1. Increased ride-hailing occupancy rate

A key variable to the base result of an increased total VKT is the occupancy rate of ride-hailing vehicles. In the simulation, average ride-hailing occupancy rate, while in passenger service, is 1.55 pax/veh in the base scenario. Now we run the simulation assuming two alternative cases in which mean occupancy rate in ride-hailing is increased to 2.0 and 2.4 pax/veh.

When mean ride-hailing occupancy is 2.0, only in 14.6% of Monte Carlo scenarios is VKT reduced, and only when the mean occupancy rate is 2.4 pax/veh, does the number of scenarios where VKT is reduced climb to 50%. Figure 9 depicts both cases, in Figure 9(a) it is shown the histogram of the 20,000 replications for the simulation of Equation 10 (which is on the horizontal axis). Alternatively, Figure 9(b) shows the cumulative proportion of cases with 2.0 and

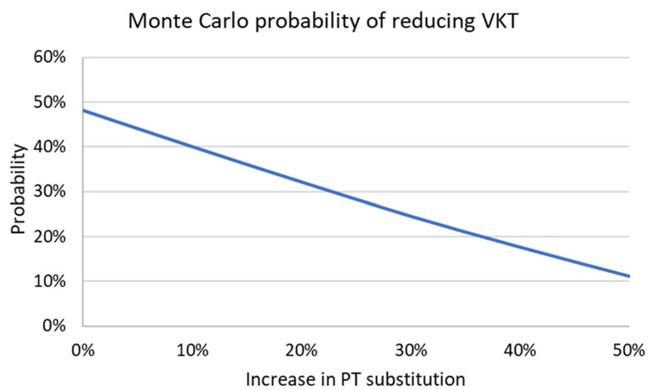


Figure 10. Change in the probability of reducing VKT due to shared ride-hailing, as a function of the increase in modal substitution from buses, relative to standard ride-hailing. VKT, vehicle kilometers traveled.

2.4 pax/veh, for the range of values of total VKT effect (Expression 10). In summary, we find that ride-hailing apps should have an occupancy rate that is between 60% and 70% larger than current taxi occupancy rate in order to have a reduction in VKT for a majority of simulated scenarios, once randomness on the relevant parameters is included in the analytical framework.

4.3.2. Increased attraction of taxi trips and reduced attraction of public transportation trips

Because of the way the survey was distributed, there might be an overrepresentation of young lower income users among respondents. Different income groups have different modal substitution rates as shown in Figure 7. We simulate a scenario in which average substitution rates are those of a higher income group, to correct for this potential bias due to the survey sampling method. Using the substitution rates for the second highest income group as the average rates for the simulation, we assume mean substitution rates to be 50.6% for taxi, 18.8% for bus and 10.7% for car (see Figure 7), the parameters are again assumed to follow a uniform distribution between 0.75 and 1.25 times the mean value. The result is that the proportion of scenarios where VKT is reduced, increases from zero to 2.0%, that is, it continues to be negligible without an increase in the ride-hailing occupancy rate.

4.3.3. The last-mile problem

In the survey there are no questions on the use of Uber as a complement of mass public transportation like the subway (metro) system in Santiago. If a trip that used to be made with a feeder mode (say bus, taxi, and private car) in combination with metro, is replaced by a trip Uber-metro, there is no bias in the analysis already performed because the effect on VKT is already accounted for. However, if an entire trip by private car is replaced by a combination Uber-metro, in this case there is a likely reduction of VKT, which is not correctly internalized in the previous analysis.

A simple way to account for this effect is to increase the average length of the car trips that are being substituted, under the assumption that a percentage of car trips are substituted by two-stage trips: a shorter ride-hailing stage plus a Metro stage that does not add vehicle-kilometers to the road network. In order to do so, we assume that car trips are between 2 and 4 times larger than the ride-hailing stage of the ride-hailing-metro that replace full car trips, and that 20% of total ride-hailing trips are in this situation. With this, average car trip length replaced by ride-hailing is between 20% and 60% larger than the average ride-hailing trip length, a value that is likely overestimating the impact on the last-mile effect on replacing full car trips. Even with this assumption, the simulation result is that the probability of reducing VKT with ride-hailing is zero.

4.3.4. Scenarios 4.3.2 and 4.3.3 combined

We then run a scenario with the assumptions of scenarios 4.3.2 and 4.3.3 combined. In this case, the proportion of scenarios where VKT falls is only 4.5%.

In summary, with our preferred set of parameters, we find that ride-hailing increases VKT by a large margin, and that including scenarios that account for expected extra benefits of ride-hailing is unlikely to change this result, unless the occupancy rate of vehicles increases significantly (Scenario 4.3.1). This finding corroborates similar results from the recent literature; for example Truong, De Gruyter, Currie, and Delbosc (2017) estimate that autonomous vehicles (AV) in Victoria, Australia, will not increase VKT only if AV occupancy rates are larger than current car occupancy rates, in the context of the growing literature that attempt to estimate the effect of AV carsharing and ridesharing on VKT and energy consumption (e.g., Brown, Gonder, & Repac, 2014; Fagnant & Kockelman, 2014; Kröger & Kichhöfer, 2017; Wadud, MacKenzie, & Leiby, 2016). This issue directs us to analyze the effect of the introduction of shared or pooled ride-hailing in our framework.

4.4. Shared ride-hailing

We include in the simulation framework the case of shared ride-hailing services, in which the same car is shared by multiple users who are not traveling together. A first issue that needs attention is finding a range of expected values for the mean occupancy rate of shared ride-hailing vehicles. Alonso-Mora, Samaranayake, Wallar, Frazzoli, and Rus (2017) simulated the operation of a fleet of shared ride-hailing vehicles in New York City; depending on fleet size and maximum acceptable waiting time, the optimization model shows that mean occupancy rate of shared vehicles with capacity of four passengers, goes from around 1.1 pax/h (larger fleet, shorter waiting time) to around 3.2 pax/veh (smaller fleet, longer waiting time). For example, a fleet of 3,000 vehicles (around 22% of current active taxis in New York City) could serve 98% of the taxi demand with an excess travel time of 2.3 min (compared to the shortest-path travel time) and mean occupancy rates up to 2.5 passengers per vehicle. A simulation of shared autonomous taxis in the city of Lisbon (OECD/ITF, 2015) shows average occupancy rates between 2.1 and 2.8 pax/veh, depending on time-of-day. In

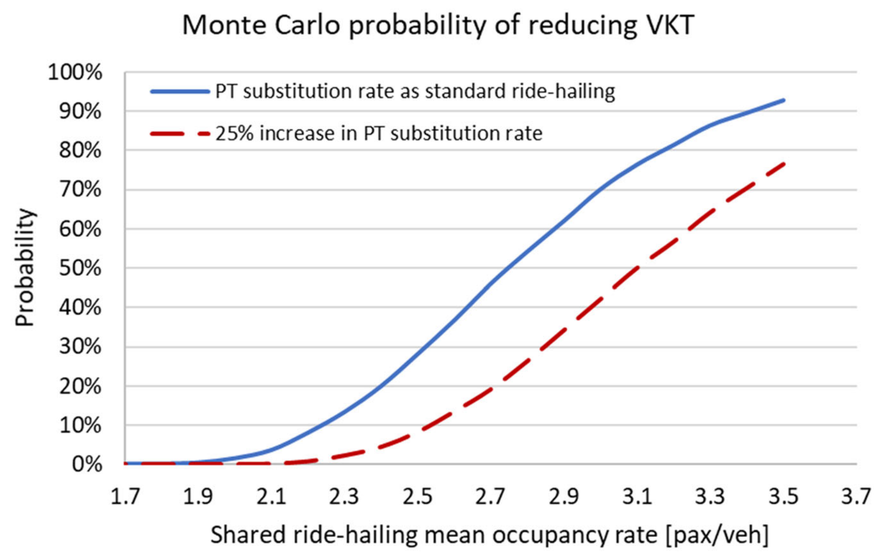


Figure 11. Probability of reducing VKT by the introduction of shared ride-hailing. VKT, vehicle kilometers traveled.

Santiago, current average occupancy rates of *colectivos* (shared taxis running on fixed routes) is between 2.2 and 3.5,[19] that is, while used, *colectivos* have an occupancy rate that is between 2.0 and 2.8 times the occupancy rates of taxis. Moreover, *colectivos* were observed without passengers between 3% and 30% of the time, compared to taxis that did not have passengers between 45% and 58% of observations.

Alonso-Mora et al. (2017) only study the substitution between current taxi trips and on-demand shared services to conclude that such a move would provide large savings in fleet size and congestion. However, as shared ride-hailing will also attract passengers from mass public transportation, this conclusion is not evident.

With shared ride-hailing, we assume that empty kilometers are between 20% and 70% of the empty kilometers of ride-hailing and that mean occupancy rate, while used, is between 2.0 and 3.5 pax/veh (similar to the values of *colectivos* in Santiago). Based on the Lisbon simulation by OECD/ITF (2015), we further assume that mean travel distance by shared ride-hailing is between 20% and 60% larger than the shortest path travel distance. Results show that with these assumptions, the proportion of scenarios that reduce VKT in this case goes up to 48%. Therefore, having shared services looks like is a key to the impact of the new mobility technologies on VKT.

The previous result has not considered differences on modal substitutions between standard (unshared) ride-hailing and shared ride-hailing. In terms of quality of service and modal characteristics, shared ride-hailing is closer to an urban bus than standard ride-hailing, since shared ride-hailing has longer waiting and in-vehicle times and lower fares than standard ride-hailing. Thus, it might not be realistic to use the same modal substitution parameters for shared ride-hailing as for standard ride-hailing. In fact, Lewis and MacKenzie (2017) find that UberHOP, a commuter type ride-sharing service, predominantly drew riders form transit services rather than private vehicles when tested in Seattle in 2016. In their study, 66% of survey respondents said that they would have relied on public transit or non-motorized modes if UberHOP were unavailable.

In order to include the different characteristics of shared ride-hailing demand when performing simulations, we have made a sensitivity analysis over the mean substitution rates, by increasing the mean substitution rate from buses to shared ride-hailing in x% (starting from the mean ride-hailing – bus substitution rate of 27.1%), for a range of values of x between 0 (mean substitution rate is 27.1%) and 50% (mean substitution rate is 40.7%). Presumably, if shared ride-hailing is closer to route based public transport than standard ride-hailing, the mean substitution rates from cars and taxis should be reduced. For the analysis, given the lack of specific data, we assumed an even reduction of $x/2$% in the substitution from taxis (40.7%) and cars (12.1%) to shared ride-hailing, therefore the total substitution as defined in Expression (11) remains unaltered. The result is presented in Figure 10, which shows a roughly linear reduction in the proportion of scenarios where VKT decreases by shared ride-hailing. Therefore, for a correct estimation of the final effect of shared ride-hailing, it is crucial to differentiate the modal substitution from other modes to standard versus shared ride-hailing.

Finally, we perform a sensitivity analysis of the likelihood of reducing VKT as a function of the mean occupancy rate of shared vehicles, as shown in Figure 11. For illustrative purposes we simulate two scenarios, first, by keeping the modal substitution parameters of standard ride-hailing as representing shared ride-hailing, and second, by increasing the substitution rate from public transport by 25% while reducing the rate from taxis and cars by 12.5%. Figure 11 shows the relevance of the occupancy rate of shared vehicles to increase the chances of having a reduction in VKT. This is so even if shared ride-hailing replaces more bus trips than standard ride-hailing. The increased substitution from buses into shared ride-hailing shifts the curve downwards, but does not change its tendency. For example, with a mean

[19]Own calculation based on SECTRA (2013).

occupancy rate of 3 pax/veh (without counting the driver), total VKT was reduced in 70% of Monte Carlo runs under the assumptions made. However, if the bus substitution rate is 25% larger than with standard ride-hailing, only 42% of Monte Carlo runs resulted in a reduction of VKT.

5. Conclusions

Many authors have pointed out the importance of determining the impact of ride-hailing on VKT (or vehicle miles traveled VMT) and thus on externalities such as congestion (Clewlow & Mishra, 2017; Henao, 2017; Rayle et al., 2016). However, to date there is scant evidence on this subject. In this paper we use survey results on Uber use by residents of Santiago, Chile, and information from other studies to parameterize a model to determine whether the advent of ride-hailing applications such as Uber increases or decreases the number of VKT. Given the uncertainty regarding some parameters, we use a Monte Carlo simulation using a range of possible parameter values to study this issue.

Our base scenario indicates that ride-hailing applications have increased VKT. This occurs because many trips made using ride-hailing services come from mass transit or are new trips (induced demand). However, as the occupancy rate of ride-hailing trips increases, the possibility that ride-hailing decreases VKT is higher. If ride-hailing becomes shared or pooled ride-hailing, in more than 50% of our simulated scenarios VKT is reduced if mean occupancy rate is 2.9 pax/veh or higher. Thus, the average occupancy rate among ride-hailing users is a key parameter that determines the impact on VKT.

It is probable that our results are conservative in terms of the positive impact of ride-hailing on VKT. Our model assumes that as users switch from transit or taxis to ride-hailing services, the supply of buses and taxis is adjusted to the new demand conditions. If this is not the case, then it is even more likely that ride-hailing applications increase VKT and thus congestion, at least until there is a supply adjustment of the other modes. However, in this case, at least for buses, there will be a negative impact on users that depend on mass transit (e.g., if they cannot afford the ride-hailing fare) since frequency or route coverage will decrease.[20] This raises issues not only on the efficiency effects of ride-hailing, but also on the equity impacts of these new mobility technologies.

Our findings point to the need to study the potential and take-up of shared ride-hailing applications (such as Uberpool and Lyft Line). In Chile some ridesharing applications are already in use ("All Ride" for example). However, to date they have had limited use among the population. We conjecture that the prior existence of a shared taxi industry, privacy and security considerations of traveling with unknown passengers, plus the absence of high-occupancy vehicle lanes in Chile (that may provide incentives for such applications elsewhere), may limit the adoption and popularity of ridesharing applications. According to our results, it is crucial to increase average occupancy rates of ride-hailing applications if these are to have beneficial externality effects, therefore further research needs to be undertaken on the variables that influence ridesharing demand, such as socioeconomic factors, trip characteristics and cost of driving, amongst other attributes (Erdoğan, Cirillo, & Tremblay, 2015).

Increased externalities due to ride-hailing applications do not imply that these services should be prohibited. The social benefits of these services in terms of customer satisfaction, lower drunk driving and other effects may more than out-weight the additional congestion or other social cost of higher VKT. However, our results do imply that regulatory mechanisms should be introduced to tackle the increased congestion caused by ride-hailing applications. Traditional supply restrictions such as quotas have been widely used in the traditional taxi sector. Although this type of regulation can have unwanted consequences, such as increasing fares, generating grandfathering rents and lower availability for consumers, it does have the merit of restricting congestion by limiting taxi supply, albeit in a very crude manner since it does not discriminate by time or geographical zone. A more efficient and sophisticated mechanism would be to use a pricing system that charges ride-hailing trips according to the congestion conditions of the time and area where the ride took place. With trip information gathered from ride-hailing applications and knowledge of the average congestion at different locations and time of day, this would be straightforward. This is the idea behind the charging system introduced in Sao Paulo, Brazil, for ride-hailing services.

Our results may seem at odds with those of Li et al. (2016), who find a negative correlation between congestion and the appearance of Uber in US metropolitan areas. They conjecture that ride-hailing applications such as Uber have the potential to reduce car ownership, increase car occupancy rates due to shared ride-hailing and delay trips during peak hours (due to surge pricing). Further research should try to reveal whether different parameter values, particularly for shared ride-hailing occupancy rates, might explain their results as compared to ours.

There are other areas for further research. Large differences in door-to-door travel time between ride-hailing and traveling by private cars do exist (Henao & Marshall, 2017), with parking time as a key factor on this outcome. Our analysis was restricted to the impact of ride-hailing on VKT; having information on travel time changes would allow us to go further by directly analyzing effects on congestion. The analytical model introduced in this paper can be adapted to the analysis of travel times in future research efforts. The implications of ride-hailing on the need for parking infrastructure and parking fees are still to be explored; seminal results on the effect of shared AVs on parking demand are promising (Zhang, Guhathakurta, Fang, & Zhang, 2015). The effect of ride-hailing applications on

[20]The effect of service frequency on reducing passenger waiting time and therefore encouraging public transportation use is known as the "Mohring effect" (Mohring, 1972).

long-run vehicle ownership decisions and their impact on externalities is another important open question.

Although ride-hailing platforms can cause negative externalities, an overall assessment of this new technology has to consider that people are revealing a preference for these services, and thus a social welfare perspective that takes into account users' benefits is necessary to complement the VKT analysis performed in this paper. Ideally, these platforms should be regulated to reduce their negative externalities, without compromising the advantages provided to users. All these issues are expected to become more relevant in a future of Mobility-as-a-Service (MaaS) as a mobility model, in which public and private modes of transport are integrated in a single platform that performs planning, booking, payment and ticketing of trips (Kamargianni & Matyas, 2017). With MaaS, larger mobility benefits and car ownership reductions may be reached, while total effect on VKT and energy consumption remains unknown. As new and disrupting mobility technologies continue to grow, it is inevitable that more research will be necessary to understand and predict their social, economic and environmental effects.

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