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Not my Usual Trip: Ride-hailing Characterization in Mexico City

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Acronyms

LAC	Latin America and the Caribbean
LATAM	Latin America
TNC	Transportation Network Company
ZMVM	Zona Metropolitana del Valle de México (in Spanish)

Contents

Not my Usual Trip:
Ride-hailing Characterization in Mexico City

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Abstract

The literature on ride-hailing has experienced rapid growth in recent years, with an accent on industrialized cities, mainly in the United States and Europe. Previous research has identified the characteristics and preferences of ride-hailing adopters in a handful of cities. However, given their marked geographical focus, whether such findings are relevant and applicable to the practice of transport planning and regulation in cities in the Global South remains largely untested.

This paper examines ride-hailing in the Metropolitan Area of Mexico City. We build on statistical modelling informed by the Mexico's household travel survey from 2017 to determine the main drivers for ride-hailing adoption, unpack ride-hailing user characteristics, and understand how they differ from other transport users in the local context. We use findings to discuss the implications of ride-hailing for urban mobility in one of the largest cities in Latin America.

Recognizing that the trajectory of adoption and development of app-based urban transport services differs from those followed in the United States and Europe, the paper hypothesizes that ride-hailing usage in a context such as Mexico may be mediated by social issues such as the perception of crime, risk of sexual harassment in public transportation, and lack of flexibility and quality in other modes. Such challenges are frequently experienced by women in this, and similar contexts as documented by the literature.

Our findings shed light on the complex role of gender and care relationships play in the adoption of on-demand transportation services. Relevant findings suggests that variables such as age, education and income have a positive effect on ride-hailing adoption, in line with the existing literature. Also, in line with current literature, we find that ride-hailing in Mexico City is instrumental for leisure and health trips. However, when considering gender, and the links between gender and care responsibilities, findings show that women in households with a higher number of elders depend more on on-demand transport. These results are novel in the context of the ride-hailing literature and suggest areas for further exploration in similar contexts to inform discussions about the role of these travel alternatives for women and their ability to navigate the city.

JEL classifications: J16, N76, O32
Keywords: Gender, Mexico, Ride-hailing, TNC.

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1. Introduction

Transport Network Companies (TNCs) are rapidly transforming the way mobility needs are being met across the globe. Also known as ride-hailing, on-demand services, and platform-based mobility services, TNC companies provide on-demand services by matching passengers needing a ride and drivers through smart phones and GPS enabled applications. Entering in 2013, TNCs have rapidly made their way into emerging and large cities in Latin America (Latam). TNCs services have been argued to offer several advantages to other modes, including relative ease use, seamless payment options, and security features. System features such route optimization, and surge pricing, that work together to direct drivers to high demand areas, have been argued to increase efficiency and reduce uncertainty over travel times and the hassle of parking (Lesteven and Samadzad, 2021). Additionally, by offering service in hours and places lacking public transit, they potentially increase mobility options in areas with poor public transit coverage, reduce the need for private auto ownership and usage, and may increase employment opportunities due to low barriers to entry (Azuara et al., 2019).

Nevertheless, policymakers have raised concerns about the possible risks for sustainable transport development, spurring debates around the potential negative externalities of rapidly growing ride-hailing on urban transportation systems, such as increases in demand for individual forms of transport, vehicle miles traveled, and congestion. Ride-hailing's virtually constant availability, demand responsiveness, and geographic coverage, unbound from routes and stations, fixed schedules (Alemi et al., 2018a; Dias et al., 2017; Etminani-Ghasrodashti and Hamidi, 2019), has also raised concerns around its impacts on public transit ridership and active modes of transport such as walking and cycling (Gabel, 2016).

Several studies in the developed countries context have looked extensively at factors influencing ride-hailing and the way people are interacting with the services. This body of literature (Alemi et al., 2018a; Dias et al., 2017; Etminani-Ghasrodashti and Hamidi, 2019) finds that comparatively younger users are more likely to use ride-hailing, and that the adoption of the service is influenced by levels of engagement with technology, as well as direct or indirect impacts of the built environment (Alemi et al., 2018c). However, large gaps in the research exist regarding the factors influencing the adoption and intensity of ride-hailing research in developing countries context where there are stark differences in levels of economic development, crime, and quality of transport infrastructure.

Many patterns of the variables influencing ride-hailing adoption are expected to be similar in the developed and developing world. For example, it is expected that younger people, highly educated people, or people with high income are using ride-hailing services more frequently. Nevertheless, a key difference to be expected is the role of gender. Current literature (not specific to the Mexican or Latam context) consistently argues that being a female has not impact on ride-hailing usage, and even that males are more likely to adopt the service. As we will show in this paper, gender is key to understand the ride-hailing trajectory in Mexico City.

In this paper, we develop a conceptual framework for ride-hailing adoption drawing on existing literature and adapting it to the particularities of Mexico City and the developing country context. The framework is empirically analyzed using a set of categorical models identifying variables that explain ride-hailing trips, as well as the variables that distinguish ride-hailing adopters from users of other transport modes like the car, public transport, or walking. Findings in the paper seek to contribute to current debates about the determinants of the use of ride-hailing and to provide insights for decision-making and policy in the local context of Mexico City.

2. Literature Review

Research to-date on ride-hailing has focused on several fronts, including identifying the factors influencing its adoption and usage patterns (Alemi et al., 2018a), measuring its impacts on travel behavior, and understanding changes in vehicle kilometers traveled (Alemi et al., 2019; Tirachini and del Río, 2019), among others. A more recent strand of literature examines the effects of ride-hailing's impacts on public transit use and modal substitutions. For example in Toronto, Canada, Young et al., (2020) estimate the degree to which ride-hailing trips complement or substitute public transit (Young et al., 2020). They modeled three outcomes based on the difference in travel times for ride-hailing trips and their transit counterpart, where simulations were used to estimate travel times. The authors found that 31% of ride-hailing trips have a similar duration to transit trips, suggesting competition. Additionally, 27% of the ride-hailing trips were more than 30 minutes faster than the transit alternative. The authors argue that, for these cases, ride-hailing is filling a gap given that these trips are too long for transit. The paper recommends creating a tax for ride-hailing trips that compete directly with transit. For Bogotá, Colombia, a study (Oviedo et al., 2020) simulate trip costs for origin destination pairs in the household surveys, and used stated-preference surveys to model potential modal shifts between public transit, private cars and TNCs under a range of scenarios. They find that nearly one-third of public transportation trips could be at risk of shifting to ride-hailing under the current public transportation fare scheme and mean travel times, and that an important share of the population is expected to be willing to pay more to reduce travel times.

In the next subsection we present a general overview of research on ride-hailing adoption highlighting the main variables that literature considers to be instrumental for ride-hailing trips. This way, we can clearly identify if there are differences or similarities with results from our models presented in section 5. In section 2.2 we move to an exploration of the gender dimension of ride-hailing and show current literature (mainly from developed countries) is consistently saying that males have higher propensity to adopt ride-hailing or that there is not a gender difference at all. We separate results related to gender given that one of the main contributions of the paper is that in the context of Mexico City, and probably in other cities in the region, gender (being a female) is instrumental for adoption. This contrasts with mainstream literature.

2.1. Ride-hailing adoption

Several authors have developed conceptual frameworks (Acheampong et al., 2020; Etminani-Ghasrodashti and Hamidi, 2019; Lavieri and Bhat, 2019) intended to explain the complexities of ride-hailing adoption. In the developed country context, a study in the Seattle Metropolitan Area (Dias et al., 2017) modeled “ride-hailing frequency” and “car-sharing frequency.” Albeit analyzing data in the early stages of operation of TNCs, they found that ride-hailing users are mainly highly educated, young, high income, and living in high-density areas- findings that have persisted in much of the subsequent ride-hailing research over time. Using Structural Equation Models SEM in the Dallas-Fort Worth Metropolitan Area (Lavieri and Bhat, 2019), a study on ride-hailing adoption and usage, showed that low residential density and concerns about privacy (mainly for non-Hispanic whites) have negative impacts on the frequency of use. Alemi et al. (2018a) studied ride-hailing adoption in the state of California, considering a diverse set of behavioral variables such as lifestyles, attitudes towards technology and pro-environmental policies, and sociodemographic variables. The model also accounted for accessibility, a mix of land use, and neighborhood type (urban, suburban, or rural). Like Dias et al. (2017), they find that ride-hailing users are young (older millennial) and well-educated people. However, their models reveal a more nuanced picture identifying clusters of adopters by their socioeconomic characteristics and land use characteristics of their residence and then analyzing how these factors influence their ride-hailing frequency.

First, they identify three main clusters of adopters: 1) high frequency adopters, who tend to be highly educated, childless, independent millennials, living in high-quality transit neighborhoods, 2) mid-level adopters-affluent millennials (or older Generation X) living with their families, who usage is often influenced by land-use mix, use of smartphones, and long-distance business trips, and 3) low-level adopters, who are less affluent, with lower educational attainment, and tend to live in rural areas and for whom the ride-hailing use is constrained by income, long-distance non-car business trips (often flights), and transit accessibility. The second extension shows that the use of smartphones and the propensity to take long-distance trips by plane is positively related to both adoption and more usage of ride-hailing, while willingness to pay more to reduce travel time and increased land use density (in residence) are related to more frequent usage.

Tirachini and Del Río (2019) modeled “frequency of use” and “occupancy rate” of ride-hailing in Santiago de Chile using ordered logistic models (Tirachini and del Río, 2019). Some results are consistent with previous literature. For example, they find that younger people are more likely to use ride-hailing more often. Nevertheless, contrary to findings in the developed country context (Alemi et al., 2018a; Tirachini, 2019), car availability did not explain frequency (when controlling for age and income). In metropolitan Teheran, Iran, a study (Etminani-Ghasrodashti and Hamidi, 2019) also modeled the frequency of use per month using a Structural Equation Model (SEM), finding cost effectiveness, security, anti-shared mobility, and technology adoption are essential determining factors. The study suggests that increased car usage is associated with more ride-hailing usage, and that ride-hailing does not necessarily imply fewer car-based trips.

Turning to a developing country, another study (Acheampong et al., 2020) conducted in Accra and Kumasi (Ghana) also using SEM showed that, similar to other studies previously referenced, that ride-hailing is mostly used for occasional trips (51%); however work and school trips also represented a substantial share of the trips (41%). Nevertheless, in contrast to other studies, the main travelers are not located on the urban side of the city but in the inner-suburban and outer-suburban localities.

2.2. Gender, transportation, and ride-hailing research

Differences in socio-economic conditions and social norms among men and women play a significant role in determining travel behavior (Curtis and Perkins, 2006)**.** These differences are even more marked in the developing country context where women take on more household and care related work and are less likely to participate in the labor market. When they do work outside the home, they are more likely to work close to their home to allow time for care-related travel and domestic responsibilities. Moreover, women trips tend to make more chained trips involving multiple stops and transfers compared to men, report making a significant number of trips for family and personal business (Schintler et al., 2000), and are more likely to travel to accompany others (such as children or the elderly), or to buy groceries and medicines, and carry packages, strollers and wheel chairs, to comply with their care work duties (Hasson and Polevoy, 2011; Soto Villagrán, 2019)**.** Lower income women tend to access to slower and lower quality modes compared to men, relying extensively on walking and public transit, even when a private vehicle is available in the household (Peters, 2013) . In addition to having distinct transport needs, women are frequently victims of sexual harassment and other crimes, often report feeling unsafe when using public transport systems (Gardner et al., 2017; Gekoski et al., 2017)

In LAC, public transit systems tend to be characterized as highly informal (Tun et al., 2020), and often lack defined stops, or security protocols and mechanisms in place to report crimes and incidents of harassment (World Bank Group and UFGE, 2020). They are also characterized as having higher rates of sexual harassment and assaults (FIA Foundation and CAF, 2017). Research on the role of investments in formal mass transit systems such as BRTs and metros that reduce travel times and include features to improve security such as cameras, guards and police at stations, and mechanisms for reporting incidents in Latin America has found that women living within walking distance to such systems are more likely to participate in the labor market and be employed suggesting that travel time savings and increased security can have an important role in improving women's access to jobs (Martínez et al., 2018).

Many studies have explored the role of gender in adoption and frequency of ride-hailing. Research on ride-hailing has explored gender in two main ways i) including gender in the analysis as a control, but not as a key variable of interest, or ii) including it as variable of interest, but finding that men are more likely to adopt ride-hailing than women, in opposition to what we hypothesize for the case of Latam. Research finding that men are more likely adopters than females are based in the USA and Canada, while there is one study showing a reverse effect in a developing country. There is little research on gender and ride-hailing in developing country context.

Descriptive research comparing socioeconomic characteristics of ride-hailing with taxis and public transit users in San Francisco (Rayle et al., 2016), although not focused on gender, presented descriptive statistics showing that males (60%) adopting ride-hailing services at higher rates than females (40%). A similar gender pattern for taxi users (who use them at least once a week) was found (42% for females and 56% for males), a striking result when considering 49% the population of San Francisco are females and 51% are males.

Alemi et al., (Alemi et al., 2018a) in their study on ride-hailing adoption and use in California found that women were slightly more likely to adopt ride-hailing compared to men and that on-demand services are higher among women, although it was not an important predictor compared to other socio-economic and built environment factors studied. An extension of the previous discussed article used Latent Class Analysis LCA (Alemi et al., 2018c) to create segments of users and explain factor influencing ride-hailing through a class membership model. Gender was not included in the class membership model of the LCA as was the case of the personal and demographic variables stage of life, marital status, income, occupation, education, and neighborhood type. Despite gender not playing a role in the model or the research, the authors mention that the share of females is slightly higher than the share of male in the class with more ride-hailing usage.

A more recent strand of research has found that males are more likely to use ride-hailing when compared to females. For example, research in the United States using National Household Travel Survey from 2017 (Mitra et al., 2019) and a logit model, found that mean were 16% more likely than women to (odds ratio of 1.159 for males (compared to females)) to use ride-hailing services. The study also highlights that men with medical conditions are more likely to engage in ride-hailing than females. A study in the Dallas-Fort Worth-Arlington Metropolitan Area (DFW) of Texas (Lavieri and Bhat, 2019) used a convenience sample of 1,607 respondents gathered through a web-based instrument and, using a structural equation model, finds that "variety-seeking attitudes" is positively associated with ride-hailing frequency of use. The gender dimension comes into play in a mediation through this latent, where males have higher levels of variety-seeking attitudes. In contrast, a recent study in Tehran (Lesteven and Samadzad, 2021) using survey data and ordered logit models shows that men are less likely to use ride-hailing, though the main determinants of adoption are income and having a smartphone.

In the LAC region, a study in the city of Santiago de Chile used a difference-in-difference model to establish the effect of ride-hailing on drunk- driving fatal traffic accidents and fatalities considering differentiating effects of males and females (Lagos et al., 2019). The results indicate that ride-hailing has decreased accidents and fatalities for all users, but mainly for female passengers, as well as among male drivers working at night. Finally, recent research in three

Mexican cities (Mérida, Toluca de Lerdo, and Aguascalientes) focusing on exclusive and pooled services and using descriptive statistics from a survey to users of a Transportation Network Company operating in the country (Moody et al., 2021), shows that the share of males (67.7%) using express services is higher than the share of females (32.3%). Despite the handful of studies that have findings regarding how gender interplays with ride-hailing adoption, very few studies explore the role of gender and ride-hailing usage in depth in the Latin American or developing country context.

3. Background and conceptual framework

The Latin American and Caribbean region (LAC) suffers from some of the highest levels of social and economic income inequality and poverty rates in the world and is highly urbanized. With average Gini index of 42 percent and poverty rates of around 30% (CEPAL, 2015), more than 80 percent the population in the countries live in cities. Urban areas in the region tend to be characterized by low quality and a lack of universal coverage of transport infrastructure services, particularly in lower income zones. Gaps in infrastructure investments combined with rapid motorization and urbanization have led to high levels of urban sprawl and congestion, and long travel times of up to 2 to 3 hours per day, and to lower levels of access and mobility, particularly for the urban poor.

A sprawling metropolis, Mexico City has undergone explosive urbanization; its population nearly doubled in the span of four decades, rising from 13 to 22 million between 1980 to 2019. Over this period much of the population moved to suburban locations while jobs remained centralized (Guerra et al., 2018) generating long commuting times and dependency on vehicles. The city suffers paralyzing levels of congestion, driven by high rates of motorization, a fragmented and largely uncoordinated public transit system, and long trip distances between origins and destinations. There are over 5 million registered vehicles and 350,000 registered motorcycles in the city (Flannery, 2019). Near 37% of the total trips in the city during a typical day are made by public transport, however, most of the trips are made using small informal operators (OECD, 2019). While the share of trips made by ride-hailing in Mexico City as well as other cities in the LAC region is still low, the individual nature of the trips combined with the fact that ride-hailing vehicles travel without a passenger for some portion of the trips, raises concerns around the level of vehicle kilometers traveled and potential impacts on congestion and public transit ridership, making understanding the patterns of use critical to planning and policies aimed at reducing their potential externalities while enhancing their value to consumers.

Crime and sexual harassment, which disproportionately affect women, are pervasive issues in Mexico City's transportation system. By 2008, 90% of women had experienced some sort of sexual violence while using public transportation in Mexico City. A recent study (Soto Villagrán, 2019) found that in some stations near 50% of women have received obscene words when using public transport, and, in one station, 6.7% have been photographed without consent. It has spurred the implementation of innovative policies like the 'pink transportation program' (Dunckel-Graglia, 2013), a transport service exclusive for women decorated with images of famous women intended to foster self-esteem, notice violence, and encourage the actions for and by women. The Pink Transportation program has been complemented with broader support to victims and was expanded to cabs.

Ride-hailing has been operating in Mexico City since 2013 with Cabify, the first TNC in arriving the city. Cabify was followed by Uber in and Lyft in 2014. As in other cities around the world, the disruption of this new mobility services created challenges in regulation. In September 2016, the government of Mexico City introduced a new tax as part of the Urban Mobility Law designed to contribute to a special trust to strengthen the city's capacity to invest in sustainable urban mobility called "Fondo para el taxi, la movilidad y el peatón" (fund for the taxi, mobility, and the pedestrian) (SEMOVI, 2019). The tax had a direct effect on the growing supply of on-demand ride-hailing services in the city as it imposed TNCs a contribution of 1.5% of the fare of each trip made using these services, a cost that was transferred to the user. Such a scheme is unique in the LAC region, and it has relevance for this research as it bears direct implications for the affordability of app-based ride-hailing compared to traditional taxis and other modes of transport.

In this section, we build on the literature review presented earlier in the paper to propose a conceptual framework explaining the factors that can influence the adoption of TNC services in urban contexts, as well as the characteristics that can distinguish ride-hailing from other transport alternatives. The framework is informed by the main features of urban transport in Mexico, although its main components reflect the main types of drivers of ride-hailing choice in the international literature. There are three starting points for the framework. First, we hypothesize that ride-hailing adopters are mainly non-frequent users of the service or those that make occasional trips during the month (Alemi et al., 2018a; Tirachini and del Río, 2019). Second, ride-hailing is unaffordable for a considerable share of the population as a frequent mode of transport. This point is expected to have greater relevance in contexts with higher concentration of poverty and income inequality. And third, crime problems and risk of sexual harassment in public transportation and public spaces may increase the appeal of ride-hailing in particular times of day, under specific circumstances, or for determined subgroups of the population. Mexico City (as other major cities in LAC) has experienced challenges associated with high rates of crime and insecurity, as well as well-documented frequent issues of harassment and gender violence in public transport and public space. While aspects of crime and gender security are likely relevant for most contexts where such services are in use, the idea that ride-hailing could be a mechanism to feel safer when traveling could have additional relevance in Global South contexts.

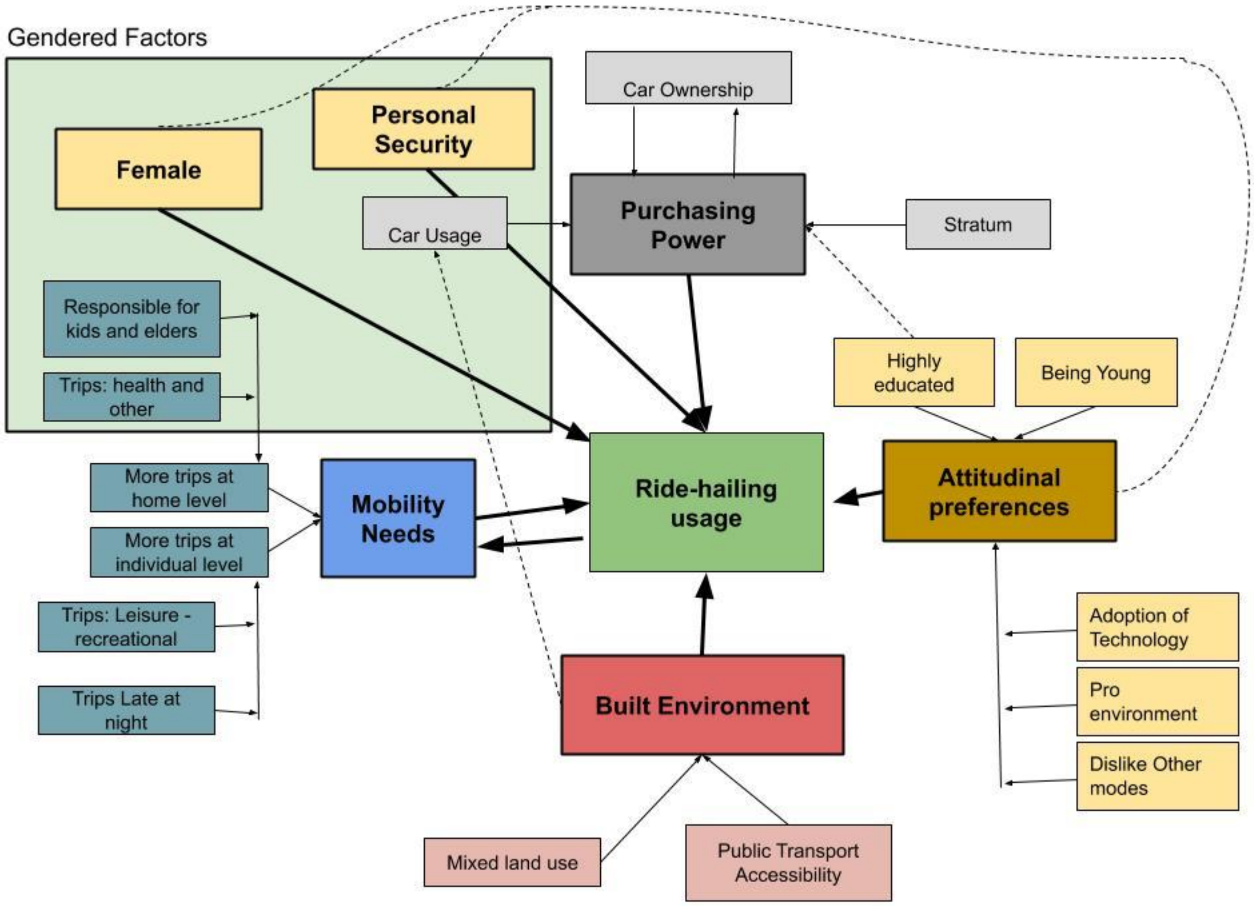

Figure 1 Conceptual Framework
Source: Own Elaboration

Additionally, our framework (Figure 1) incorporates four dimensions that have been suggested by previous research to influence patterns of use of ride-hailing: i) the *Built Environment, ii) Individual Mobility Demand, iii) Purchasing Power, and iv) Attitudinal Preferences*. This group of variables is complemented with the *gender* of the person and with factors affecting *Personal Security* as one of the conceptual contributions of this article. It is also important to highlight that our proposed models are heavily influenced by life stage and household composition (Janke et al., 2020). In Figure 1, thick lines are interpreted as having a direct effect and dashed lines as having a mediated effect. For example, purchasing power and attitudinal preferences are directly affecting ride-hailing adoption. Concerns about personal security can directly affect ride-hailing as well as shape attitudes that ultimately influence ride-hailing. In the first case there is a thick line from personal security to ride-hailing adoption, and in the second case there is a dashed line from personal security to attitudinal preferences and late a thick line from attitudinal preferences to ride-hailing usage.

3.1. Built Environment

The built environment, which encompasses infrastructure and urban form, influences ride-hailing usage and patterns through several mechanisms. First, the degree of quality and coverage of public transport infrastructure and services (Alemi et al., 2018a; Dias et al., 2017; Etminani-Ghasrodashti and Hamidi, 2019) can influence ride-hailing usage in two ways. For high-income individuals who live near public transit stations, public transportation may serve their usual trips such as work or school, while ride-hailing may serve many of their non-usual ones, such as attending social events or seeing a doctor, and to more dispersed locations or at times not well served by public transit. In areas with high levels of congestion and limited parking, combining public transportation and ride-hailing services may potentially reduce car-ownership by providing a flexible alternative that offers the comfort of the car when needed without the added burden associated with owning it. Conversely, those living outside of mass transit hubs or in transit desserts and/or for those without access to private vehicles (households that share a vehicle), ride hailing may serve occasional trips not easily reach on foot or by transit.

Second, areas with high degrees of land use mix and density may have either downward or upward effects on ride-hailing demand (Marquet, 2020). People living or working in dense mixed-use areas with more opportunities clustered together, might prefer walking or biking instead of using TNCs for short trips, generating a downward effect. The upward effect is like that of public transportation discussed before. If travelers can reach many destinations on foot or without relying on owning a private vehicle, they may forgo auto ownership altogether and use ride-hailing for the trips that go beyond walkable or transitable distances. In addition, among those who do own cars, parking restrictions in denser mixed-use areas may induce ride-hailing amongst travelers looking to save time and hassle searching for parking and to save on parking costs. Conversely, investments in high quality public infrastructure can spur more mixed land used and reinforce the cycle of walking or cycling for short trips and ride-hailing for longer trips. Finally, higher rates of auto-dependency may occur in low-density and single use zones that impose long distances between origins and destinations, and an urban form that is difficult to serve efficiently through mass transit. Although car dependent urban forms can reduce the overall demand for ride-hailing, in these environments, it may be an attractive back up to the car in many instances.

3.2. Mobility Needs

The dimension of mobility needs encapsulates the different trips that people perform. Individuals living in households with more diverse and intensive mobility needs are more likely to, eventually, perform more ride-hailing trips because they cannot perform all the trips in the same transport mode. For example, trips with baggage, to medical appointments, or with children are not as easy to conduct in public transportation as in ride-hailing. In addition, personal mobility matters, as do the needs of other members of the household. A reason for this is negotiations at the household level about the distribution of budgets and access to the car (Levy, 2013a; Schwanen, 2011). Something that we consider a crucial element is the role of people in charge of elders or kids. Ride-hailing might look like a more appealing alternative when traveling with elders or children than regular public transportation.

3.3. Attitudinal Preferences

Preferences are expected to vary across various levels of education and age. For example, the level of engagement in technology (Fu, 2020; Kong et al., 2020), the literacy to use it, and the trend towards being an early adopter. Moreover, the use of a TNC app demands basic knowledge about technology, such as knowing how to create an account, how to make electronic payments, or how to navigate an interactive map to input trip origins and destinations. Amongst younger and highly educated individuals, this is likely common knowledge, but for older cohorts, it may present a challenge that may constrain their use of ride-hailing.

A second dimension we consider is attitudinal preferences towards the environment, which can affect ride-hailing adoption in two ways. On the one hand, individuals with pro-environment attitudes might avoid using ride-hailing services, given that the service may have similar environmental consequences to those of driving a personal vehicle. On the other, this group may avoid owning a car and make their frequent trips in more sustainable alternatives such as public transit and walking and use ride-hailing for the non-frequent trips that are not easily made in these alternatives.

Finally, attitudes towards different transport modes are likely to differ in Latin America compared to other contexts examined in the academic literature. Not only travelers may have negative perceptions regarding the quality and or security of public transport modes derived from previous experiences. In Mexico City, similarly to other contexts in LAC, the use of public transport, and to some extent walking and cycling, are associated with differences in class and income, and often avoided by higher-income residents (Gandelman et al., 2019; Guerra et al., 2018; Jauregui-Fung et al., 2019). In Mexico, where the backbone of the transport system is composed of Jitney-semi-informal minibus services that are characterized as low quality, non-reliable, and insecure (Flores-Dewey, 2019), tendencies of positive associations of car ownership with status and power are more likely to manifest alongside an increasing use of collective transport by groups with lower purchasing power (Gallego et al., 2013). Other key issues are fear of crime and sexual harassment, both of which are disproportionately experienced by women (Dunckel-Graglia, 2013; Dunckel Graglia, 2016).

3.4. Purchasing Power

Ride-hailing is an expensive service relative to other transport modes in Latin American cities. Particularly in the developing country context, where high rates of inequality and poverty are persistent, ride-hailing may be unaffordable for a substantial part of the population. Initial proxies for purchasing power are the socioeconomic stratum of the zone where the person lives. Stratum is Other important proxy is the level of education, with more educated individuals expected to have higher average incomes than those with lower levels of education (Ferreyra et al., 2017). Education is a variable that affects two dimensions (purchasing power and attitudinal preferences) of ride-hailing use and is expected to have significant relevance in explaining ride-hailing.

Finally, car ownership has theoretical two principal influences on ride hailing. People in the right economic conditions can buy cars, which can reduce demand for ride haling but may also increase it where car usage is expensive (parking). Also, in some contexts, people with a private vehicle can have access to employment opportunities that are not available in other transport modes, which in turn increases available disposable income.

1.2. Gendered Factors

The variable, *gender,* is expected to be significant in most of the models we present later in the article. At the top left of Figure 1, the square “Gendered Factors” is not a dimension itself. Instead, it is a common area of variables from the aspects discussed here that overlap with gender. Because of the typical role that woman play related to household care related activities, their travel patterns tend to distinct from those of men (BID, 2018). Typically, women’s travel is more complex due to their tendency to oversee more of the household related shopping and typical increased responsibilities related to care of children and elders. Compounding these trends, they have access to lower quality and slower modes of transport and access to the private vehicle in households leans towards the working-male, leaving women with the need to look for alternative modes of travel (Levy, 2013b; Schwanen, 2011). Moreover, gender-based violence deserves special attention when studying the ride-hailing phenomena in Mexico City. Given the high rates of crime and sexual harassment in Mexico City, as mentioned previously, the government has developed strategies to increase safety and security form women, but with limited success (Dunckel-Graglia, 2013; Dunckel Graglia, 2016).

The combination of more complex mobilities, less access to use the car in the household, and being fearful to public transport, may lead women with the economic capacity of affording ride-hailing to turn to it as an alternative mode.

In summary, the models proposed for this article (see section 4 for the variables used in every model and section 5 for the results) are based on the conceptual framework presented, in order to assess the validity of hypotheses posed including 1) that gender is a key variable for the adoption of ride-hailing, 2) that younger people with high educational attainment are more likely to use ride-hailing, and 3) that the built environment should explain some share of ride-hailing trips. In the models, we do not include variables expressing attitudinal preferences and subjective perceptions of fear of crime due to the lack of these variables in the survey we used for the models.

4. Data and methods

We use the most recent Household Transport Survey HTS in Mexico City (2017) to run two types of categorical models of ride-hailing adoption. First, we employ a logistic regression to understand the factors influencing ride-hailing adoption, with the outcome variable being whether an individual is a ride-hailing user or not (defined as performing at least one trip on a weekday or weekend). Our second model is a multinomial logistic regression that measures the impacts of different factors in our conceptual framework on mode choice between ride-hailing versus other modes. The outcomes include a set of transport modes available in the city, with ride-hailing assigned as the base outcome. In constructing our models, we draw upon the conceptual framework presented in the previous section and the availability of information in the HTS. Next, we present an overview of the dataset used and the mathematical logic of the models.

4.1.. Household Travel Survey

The 2017 travel survey for Mexico City include 142,415 persons in 66,625 households, living in 195 districts that encompass the metropolitan area of Mexico City, (frequently referred to as the Valley of Mexico Metropolitan Zone ZMVM (Zona Metropolitana del Valle de México, in Spanish)). Only respondents six years and older could answer the survey and provided detailed information about their trips performed the prior week for a randomly chosen weekday (Tuesday, Wednesday, or Thursday) and Saturday.

For our analysis, the dataset is grouped into ride-hailing users (1,522 respondents) and non-users (140,893 respondents) as shown in Table 1. We define a ride-hailing user as an individual that reported at least one ride-hailing trip during the weekday or on Saturday. We construct three variables to measure characteristics of the built environment of the district of residence of the travel survey respondents, Transit Intensity, Trips within District, and Distance to Center. *Transit intensity* corresponds to the proportion of public transport trips (considering all public transport modes) relative to all trips made within a given district (considering all modes). *Trips within district* of residence is a measure of the total trips in the sample that originate in one district and finish in the same district. Distance to the center is the distance from the centroid of each district to the Central district of the zone of study (ZMVM). Transit intensity, Trips Within District and Distance to Center variables are defined at the district of residence of each individual. We calculate the quartiles for each of these variables. Finally, Strata is a commonly used proxy for income and socio-economic levels in the Latin American context (Cantillo-García et al., 2019). The variable assigns a value from 1 to 4 to assign a household's socioeconomic status building on a combination of socioeconomic and housing characteristics. As an aggregate measure, it provides only an approximation based on the quality of housing materials and available facilities, as well as aspects of individuals in the household associated with income. Strata 1 is often associated with lower-income households and 4 corresponds to the highest socioeconomic status.

Table 1. Characteristics of the sample

		Non-Users vs ride-hailing users	
		Non-Users	Users
Observations		140,893	1,522
Variables:		%	%
Sex	Male	48.42	41.98
	Female	51.58	58.02
Age	(10 - 15)	7.99	4.14
	(15 - 20)	9.91	9.46
	(20 - 30)	20.27	30.88
	(30 - 40)	18.89	21.75
	(40 - 50)	17.56	13.73
	(50 - 60)	13.45	10.38
	(>60)	11.93	9.66
Education Level	Low	48.41	19.84
	Middle	29.58	26.15
	High	22.00	54.01
Stratum	1 (Low)	0.86	0.13
	2 (Medium)	57.04	26.22
	3 (Medium/High)	30.46	42.12
	4 (High)	11.64	31.54
Transit Intensity	Low	25.34	16.75
	Medium	25.49	21.22
	Medium/High	24.96	31.60
	High	24.20	30.42
Trips Within District	Low	21.57	51.25
	Medium	25.21	24.44
	Medium/High	26.29	14.32
	High	26.93	9.99
Distance to Center	First Ring	23.53	46.19
	Second Ring	24.51	26.61
	Third Ring	26.01	20.63
	Fourth Ring	25.94	6.57

Source: Own elaboration based on 2017 household travel survey for Mexico City

Notes: Transit Intensity quartiles: 1st quartile goes from 1.9% to 30.5%; 2nd quartiles from 30.5% to 34.5%; 3rd quartile from 34,5% to 38.9%; and 4th quartile from 38.9% to 64%. Trips Within District quartiles are as follows: 1st quartile includes from 1.3% to ,31.3%; 2nd quartile from 31.3% to 38.8%; 3rd quartile from 38.8% to 46.8%; and 4th quartile from 46.8% to 85.7%. We calculate distance to center and report by quartiles, where the 1st quartile goes from 0 Km to 1.1 km; the second quartile from 1.1 km to 16.2 km; and the 3rd quartile from 16.2 Km to 24.8 Km; and the 4th quartile from 24.8 Km to 59.2 Km.

Table 1 presents characteristics of variables used in our models and how they relate to ride-hailing adoption and intensity. Although there are more females than males in the survey, there is a slight increase in ride-hailing users who are female (58.0%) compared to non-user females (51.6%). In terms of age, ride-hailing users have more people between 20 and 30 years old (30.9%) than non-users (20.3%). 48.41% of the non-users and 19.8% of users have a low level of education.

Transit intensity is relatively equally distributed among the four categories in the case of the non-users, with around 25% in each group. The case of the users is different, and it is skewed towards more presence in the Medium/High category and the High category with 31.6% and 30.4%, respectively. Trips within District and distance to the center have a similar pattern. Additional information about variables in the survey is presented in appendix A.

In the annex we include descriptive statistics for each of the modes where is possible to observe that ride-hailing is composed mainly of door-to-door trips (trips with just one stage), with 91.69% of trips being a one-stage trip.

In Figure 2 we present the share of trips by gender according to all the purposes included in the transport household survey. The plot at the top includes all the modes whilst the plot at the bottom retains only ride-hailing trips. In general terms, males (63.12%) make more work trips than females (36.88%) when all modes are analyzed, but the proportion reverse for ride-hailing trips with males making 44.17% of the work trips and females 55.83%. This could be an indication that ride-hailing is, at some extent, being more instrumental for women than it is for men. In both plots women make more health trips as well as other trips.

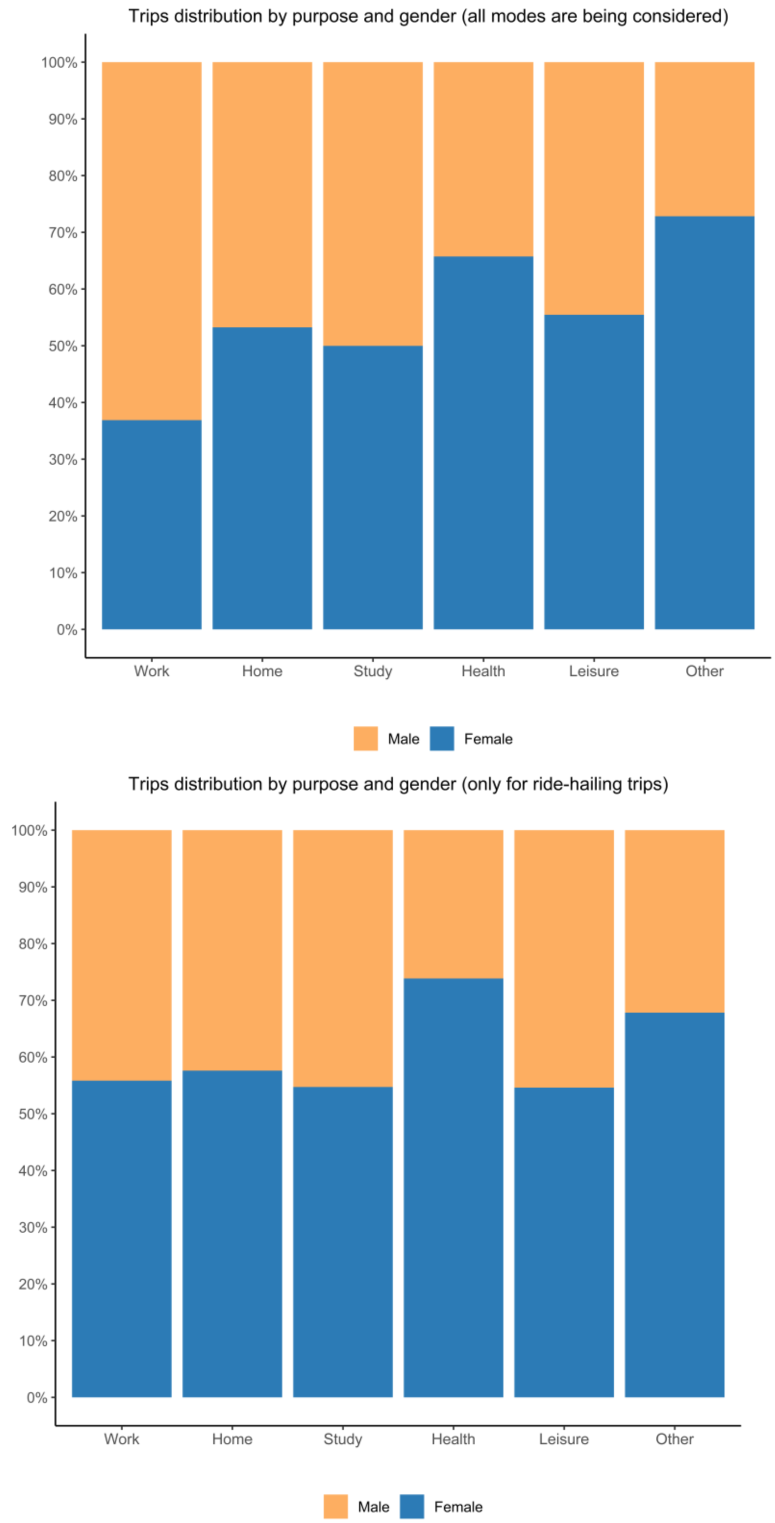

Figure 2 Trips distribution by purpose and gender
Source: Own Elaboration

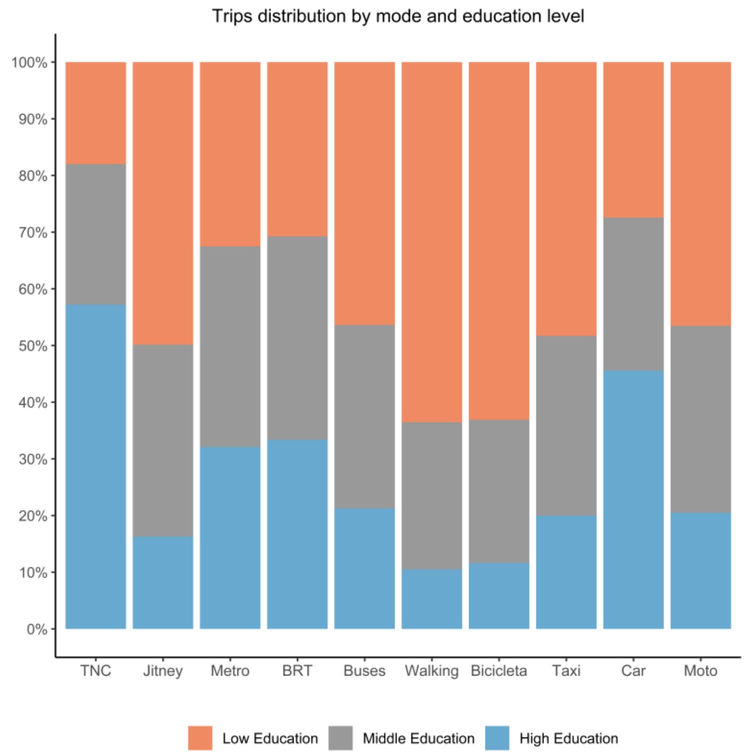

Figure 3 Distribution of trips by mode and education level
Source: Own Elaboration

As mentioned before, prior literature has consistently found that higher levels of education are associated with ride-hailing adoption. A similar pattern is found for Mexico City (see Figure 3) where 57.2% of TNCs users are highly educated, a number way above the percentage of highly educated people for all the other modes. The closest mode is car with 45.56% of car users being highly educated. The differences with all other modes are extremely large. For example, only 16.29% of Jitney commuters and 32.08% of metros users are highly educated. The categorical models presented later also show that higher levels of education are related to engaging with ride-hailing.

Household travel surveys have been used in the past to study ride-hailing. For example, Dias et al., used the Puget Sound Regional Travel Study (Dias et al., 2017) and Jiao et al., used the National Household Travel Survey (NHTS) from the United States (Jiao et al., 2020). In Toronto, a study (Young et al., 2020) combined the 2016 Transportation Tomorrow Survey TTS with OpenTripPlanner and GTFS to simulate travel times in different transport modes and make comparisons with simulated ride-hailing trips. Also in Canada, another study (Habib, 2019) used the TTS to investigate competition between Uber and other transport modes in the Greater Toronto and Hamilton Areas.

4.2. Categorical Models

Turning to the modeling framework, the first model employed is at the individual level and is a binary logistic regression where the outcome variable is one if the person is a ride-hailing user (as specified for Table 1) and zero otherwise. Mathematically, the logistic model has the following form,

$$logit(\pi(x)) = log\left[\frac{\pi(x)}{1-\pi(x)}\right] = \alpha + \beta * x \qquad (1)$$

$$\pi(x) = \frac{e^{\alpha + \beta * x}}{1+e^{\alpha + \beta * x}} \qquad (2)$$

where $logit(\pi(x))$ is the link function, α the intercept parameter, β a collection of estimated parameters and x is a vector of covariates including built environment and demographic variables, as discussed above.

The logistic model includes all variables in Table 1 plus occupation, relationship with the head of household, vehicles in the households, number of children and elders in the household. Other variables included to capture the complex mobility of each person were, i) percentage of trips per different purposes (considering the weekday trips and the Saturday trips), ii) percentage of trips at night, iii) total trips made by the entire household in a weekday, and iv) trips made by the household on Saturday.

The second model, the multinomial, is a generalization of the logit model that allows the outcome variable to have more than two categories. For our case, the outcome variable is the primary mode used for each trip performed by the respondent, where in the case of car the traveler could have either traveled as a passenger or as a driver. The multinomial model has a similar specification to the one used for the logistic model, though there is a significant change. Since the unit of analysis is at the trip level, we included the built environment variables by origin and destination. We include for example, Transit Intensity for the District where the person lives but also the Transit Intensity of the trip where the specific journey started and the Transit Intensity for the District where that same trip ends. Moreover, we included travel time of each trip and an interaction between gender and elders in the household.

5. Results

5.1. Ride-hailing adopters vs. non-Adopters

The results for the logistic model of ride-hailing adoption are presented in Table 2. Several demographic variables are important determinants of ride-hailing adoption. As expected, and discussed in the conceptual framework, gender is a significant variable, with the odds ratio of making ride-hailing trips increasing by 34.9% if the traveler is a female (with reference to male). This finding (an others from the multinomial model presented below) is different from standard literature that has suggested that gender is not important or that males are more likely to engage in ride-hailing. We think that this difference constitutes the main particularities of the ride-hailing phenomena in Mexico City.

For the age variable, we assigned the category between 20 and 30 years old as the reference category. As age increases, the magnitudes of the estimates reduce. This suggests that older generations are least likely to adopt ride-hailing services and is similar to findings in international literature. Interestingly, the age cohort between 10 and 15 years old increases the likelihood of adopting ride-hailing services (odd ratio equals to 1.375). This could be an effect of parents relying in TNCs to guarantee mobilities for their children.

Table 2. Factors influencing ride-hailing adoption

	Estimate		Estimate
Gender		Percentage Home Trips	0.514*** (0.086)
Male	reference reference	Percentage Work Trips	0.924 (0.172)
Female	1.349*** (0.082)	Percentage Study Trips	0.560** (0.163)
Age		Percentage Leisure Trips	3.808*** (0.622)
(10 to 15)	1.375* (0.242)	Percentage Health Trips	9.908*** (2.454)
(15 to 20)	1.152 (0.132)	Percentage Other Trips	1.094 (0.208)
(20 to 30)	reference reference	Percentage of Night Trips	2.189*** (0.240)
(30 to 40)	0.722*** (0.058)	Strata	
(40 to 50)	0.527*** (0.051)	Stratum 1	reference reference
(50 to 60)	0.482*** (0.052)	Stratum 2	1.506 (1.073)
>60	0.466*** (0.067)	Stratum 3	2.421 (1.727)
Occupation		Stratum 4	3.805* (2.721)
Employed	reference reference	Cars in household	0.793*** (0.029)
Had a Work but did not work	1.174 (0.369)	Motorcycles in household	1.063 (0.087)
Unemployed - Looking for a job	0.395*** (0.135)	Kids (under 5 years)	0.953 (0.052)
Student	0.924 (0.112)	Elders (Above 65 years)	0.989 (0.053)
Househusband/housewife	0.892 (0.096)	Trips in Weekday (Home Level)	0.971*** (0.010)
Retired	0.883 (0.135)	Trips on Saturday (Home Level)	1.007 (0.012)
Cannot work for life	0.963 (0.407)	Transit Intensity	
Does not have a job	0.855 (0.116)	Low	reference reference
Education		Medium	1.024 (0.094)
Low Educated	reference reference	Medium/High	1.168* (0.102)
Medium Educated	1.665*** (0.143)	High	0.958 (0.085)
High Educated	3.409*** (0.294)		

Relationship with the head of household		Trips Within District	
Head	reference reference	Low	reference reference
Partner	1.022 (0.090)	Medium	0.641*** (0.045)
Son/Daughter	0.908 (0.082)	Medium/High	0.491*** (0.045)
Grandson/granddaughter	0.972 (0.181)	High	0.585*** (0.070)
Other	1.255** (0.138)	Distance to Centre (District of the HH)	
No kinship	1.894*** (0.364)	First Ring	reference reference
Trips on Saturday (Individual)	1.235*** (0.039)	Second Ring	0.852** (0.060)
Trips on Weekday (Individual)	1.066** (0.031)	Third Ring	0.744*** (0.060)
		Fourth Ring	0.317*** (0.041)
		Constant	0.005*** (0.004)
Observations	142,415		

Notes: Adoption refers to using a TNC at least once in the reference week. Results from logistic model. Odds ratios are presented. P values were calculated with original estimates. Statistical significance as follows: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Chi Square for the model: 2161.88***. Pseudo R2 for the model: 0.13.
Source: Own elaboration based on 2017 household travel survey for Mexico City

As many previous studies in developed countries have highlighted, education is also one of the more influential variables on ride-hailing adoption in Mexico City. Compared to less educated individuals, those with more education are significantly more likely to adopt ride-hailing, with an estimated increase of 66.5% (statistically significant at the 1% level) in using ride-hailing for medium educated users and by 241% (statistically significant at the 1% level) for high educated users. The coefficient for the number of trips a person performs suggests that for an additional trip in a weekday, the odds ratio of using ride-hailing against not using it grows by 6.6%, but for extra trips on a Saturday, the growth is substantially more (of 23.5%). It is important to note that there could be an endogenous relationship here in which the availability of ride-hailing could increase the demand for mobility or meet latent demand.

In terms of trip purpose, the percent of household trips to return home or to study is statistically less likely to be made in ride-hailing. Tours with the purpose of study, work, or come back home are considered regular trips. On the other hand, leisure, and health tips, as well as trips at night, are connected to less frequent trips or random trips. This group of variables has a positive effect on ride-hailing use, a finding also connected to previous literature and reflecting that ride-hailing is instrumental for not usual trips

Also, in line with international literature, the highest stratum is one of the main variables explaining ride-hailing adoption. Stratum 4, when compared to Stratum 1, has an effect of 3.805.

Transit intensity in the district of residence does not have any effect on ride-hailing use in the week prior. However, the estimates for distance to center and trips within district variables suggest that living closer to the center increases the probability of ride-hailing adoption. People living in districts far away from the city's historical center are less likely to use ride-hailing. Relative to the first ring, those living in the second ring, are estimated to have an odds ratio of 85.2% and among those living in the fourth ring the odds decrease to 31.7%.

We tested additional models adding interactions between gender and other key variables such as number of children in the household, elders in the household, stratum, and education level. Nevertheless, results were not significant, and all the other estimates remained similar indicating that gender impacts on ride hailing may be mediated through more complex factors such as quality and coverage of public transit or other available modes, built environment, and perceptions of security and vulnerability.

5.2. Ride-hailing vs. other modes

In Table 3 we present the results of the multinomial model estimation. For brevity, we present a reduced version of the full output, including mostly the main, statistically significant results. In the appendix C we show the full version of the output. Recall that for this model the outcome variable is the individual level primary mode for a given trip.

Results for gender are not significant for Jitney, BRT, and Walking. Only for the case of Taxi being a female reduces the probability of ride-hailing (odds ratio of 1.3), in all the other modes the estimate is significant and towards the opposite direction. For Metro and Bus gender has the higher effects on increasing the likelihood of ride-hailing: 78.4% for Metro and 89.9% for Bus if the person is a female. Car has and odds ratio of 55.3% while Cycling and Moto show the lower effect with 0.208 and 0.222, respectively. These results complement findings from the logit model and provide more evidence that, in contrast to standard understanding of ride-hailing, gender is an important determinant in the Mexican context.

The interaction between gender and number of elders in the household show heterogeneous results across modes, but it enables a deeper look at how ride-haling is relevant for mobility of women. With the coefficient for car being the only not significant, all the other coefficients show high impacts in favor of ride-hailing. The lower odds ratio is for cycling (0.499). Al the other odds ratios are around 0.8. These results are suggesting that ride-hailing is being instrumental for the care mobilities of women. In other words, women are probably more responsible of taking care of elders in the household, and ride-hailing is a transport alternative that fits that need.

Like results found in the logistic regressions, younger generations are more likely to use TNCs compared to any other transport mode. The age group between 10- and 15-years old is less likely to use Jitney, Metro, BRT, Bus, Cycling, and Moto. The only mode that is more likely to be used than ride-hailing in this cohort is Car. The age cohort between 15- and 20-year-old have a similar pattern but higher odds ratio; moreover, estimate for BRT and car are not significant. These results suggest that younger generations are already showing more positive perceptions towards ride-hailing. Another interpretation is that parents are using TNCs to provide mobilities (mainly for the 10- to 15-years old cohort) in a perceived safer environment where their children's location can be tracked via apps.

In contrast, older cohorts are more likely than younger ones to prefer modes other than ride-hailing. All else equal, if a person is in their thirties, forties, or fifties (using the cohort between 20 and 30 years as the reference category), then the use of any transport mode other than TNCs is the most likely outcome, with motorcycle being the only exception. For example, for people between 50 and 60 years old, the odds ratio of using Metro over TNCs increases by 1.888. Interestingly, the motorcycle is the only mode where these patterns reverse, showing that users in the 40- to 50-year-old group and the 50- to 60-year-old group reduce the odds ratio of using moto by 84.5% and 63.7%. This output may be associated to risk perceptions and not with a preference for ride-hailing.

For those occupied as a househusband/housewife (relative to employed outside the home), the relative odds of using public transport modes (Metro, BRT, Bus) and private vehicles (car and motorcycle), instead of ride-hailing decreases but increases for the case of walking (1.560 odds ratio). As expected, unemployed individuals that are active job seekers are very reluctant to use ride-hailing and they are more likely to use public transportation or walking. The category “cannot work for life” (than can be associated with disabilities) decreases the odds ratio of using Jitneys, Metro, or Bicycle relative to ride-hailing (compared to those who are employed), indicating a preference for ride-hailing among this group (see appendix). The estimates of the effect of education on ride-hailing behave similarly to those for the logit model. Using the low-level of education category as the reference, the two categories -medium and high levels of education -are greater than one and statistically significant across all the modes, suggesting a preference for ride-hailing over other all the other modes amongst those with higher levels of education.

The coefficients for trip purposes (work trips as reference) show that ride-hailing is preferred over virtually any other mode for health and leisure trips. The relationship with the head of household also has an influence on mode choice. Those who reported being the partner of the household head were more likely (compared to the household head) to choose walking (15.4% more) instead of ride-hailing. This suggests that partners of the head of household have more mobility needs that are reachable without the need of ride-hailing services or they are less likely to have access to a vehicle in the household. For the categories of Son/Daughter and Grandson/Granddaughter, all the other modes are favored (with the car being the only exception) above ride-hailing.

The individual activity variables show that increased trip activity on a Saturday slightly increases the odds ratios of car (1.153) and motorcycles (1.175). The estimate for taxis is showing a positive effect (1.139). One more trip on a weekday has a similar impact, but the estimate is also significant for Jitney, Bus, and Walking. Also, the night trips variable has odds ratio estimates between 0.294 (Cycling) and 0.751 (Car).

The effect of socioeconomic strata on ride-hailing in this set of results do not appear to be as salient as in the logistic model results (see appendix). However, relative to the lower socioeconomic strata (strata 1), individuals in Stratum 4, the highest strata, are much more likely to use ride-hailing over Jitney, Metro, BRT, Walking, Cycling, and Moto. In terms of private vehicle ownership, however, the impact of having one more private vehicle (car or motorcycle) decreases the odds ratio of using any other mode in the model. For example, the estimate for motorcycle is 0.508 in Jitneys and 0.624 in metro, meaning that those with private vehicles in their households are less likely to use either a Jitney or the metro over ride-hailing for their trips. As expected, the number of cars and motorcycles in the household increases the probability of trips (relative to ride-hailing) made in those modes, with estimates of 3.480 and 13.523, for car and motorcycle, respectively.

Now we move to the interpretation of the built environment variables (see appendix). In the multinomial model there are two important conceptual changes. The model does not only make specific comparisons of ride-hailing trips with trips from other modes, as the data is at the trip level the model includes the built environment variables for the origin and destination of the trip and therefore, but a more detailed view on the urban form impacts can also be found. This is the case of the transit intensity variable that does not seem to be relevant in the full logistic model, but that brings additional results in the multinomial. High Transit Intensity in the origin or destination of the trip increase the odds ratio of using public transportation above ride-hailing. For the origins, the High intensity category estimates are 1.455 for Jitney, 2.328 for Metro, 1.431 for BRT and 1.419 for Bus, and for the destination, Jitney (1.381), Metro (2.108), and BRT (1.283). The results are similar for the transit intensity in the destination (except for bus that is not significant). In conclusion, better levels of public transport provision are associated with less TNC trips.

The trips within district variable (that can be considered as a proxy to land-use diversity and/or population density) shows a pattern of increasing usage of jitney and buses (compared to TNCs) in zones with medium and high trip intensity categories relative to low trip intensity zones, but decreasing use of walking, cycling and taxi relative to TNC trips. When analyzing the characteristics of origin and destination of the trips, we can observe a different pattern. For example, if a person lives in a medium/high or high trip-within-district area then the estimates of the odds of using public transit instead of ride-hailing increases. For example, in the case of metro (versus ride-hailing), the relative propensity increases to 12.823 and 8.662, respectively. But if the trip starts in a medium/high or high trip intensity district the odds for metro decrease to 0.408 (medium/high) and 0.524 (high) and the odds of walking or cycling increase. If the trips end in a medium or high trip intensity destination the odds are similar, 0.403 and 0.527, respectively.

Lastly, people living further away from the city center have a higher likelihood of using Jitney compared to ride-hailing. For the case of BRT, living in the second and third rings increases the likelihood of using ride-hailing by 59% and 59.2% (respectively), though the odds ratio are in favor of BRT in the fourth ring (78.4%). If the trip starts or finishes beyond the first ring, the direction of the odds ratio leans towards Jitney.

Table 3. Influence of individual and trip-level characteristics on ride-hailing modal choice

	Jitney	Metro	BRT	Bus	Walking	Cycling	Taxi	Car	Moto
Gender (reference: male)									
Female	0.950 (0.053)	0.784*** (0.045)	0.992 (0.062)	0.899* (0.054)	0.973 (0.055)	0.208*** (0.013)	1.300*** (0.077)	0.553*** (0.031)	0.222*** (0.017)
Female * Elders (Above 65 years)	0.807*** (0.061)	0.812*** (0.063)	0.839** (0.070)	0.760*** (0.062)	0.789*** (0.060)	0.499*** (0.046)	0.820** (0.065)	0.991 (0.075)	0.778** (0.089)
Age (reference: 20 to 30)									
(10 to 15)	0.441*** (0.068)	0.308*** (0.049)	0.381*** (0.066)	0.399*** (0.066)	1.003 (0.154)	0.382*** (0.065)	0.806 (0.129)	1.823*** (0.281)	0.209*** (0.041)
(15 to 20)	0.812** (0.080)	0.786** (0.080)	0.864 (0.094)	0.699*** (0.075)	0.910 (0.091)	0.699*** (0.077)	0.748*** (0.079)	0.890 (0.089)	0.509*** (0.062)
(30 to 40)	1.163** (0.077)	1.150** (0.079)	0.970 (0.074)	1.113 (0.082)	1.211*** (0.081)	1.213*** (0.090)	1.282*** (0.091)	1.778*** (0.118)	0.931 (0.074)
(40 to 50)	1.667*** (0.133)	1.509*** (0.124)	1.397*** (0.125)	1.513*** (0.131)	1.643*** (0.132)	1.765*** (0.154)	2.010*** (0.169)	2.455*** (0.196)	0.845* (0.081)
(50 to 60)	1.902*** (0.172)	1.888*** (0.174)	1.795*** (0.180)	1.972*** (0.192)	2.091*** (0.190)	1.997*** (0.196)	2.524*** (0.238)	2.335*** (0.211)	0.637*** (0.073)
>60	1.865*** (0.230)	1.995*** (0.251)	1.732*** (0.237)	2.111*** (0.280)	2.359*** (0.291)	2.013*** (0.268)	2.809*** (0.358)	2.575*** (0.316)	0.232*** (0.042)
Occupation (reference: employed)									
Unemployed - Looking for a job	2.401*** (0.681)	2.506*** (0.719)	2.178** (0.659)	2.267*** (0.670)	2.980*** (0.847)	2.401*** (0.705)	2.380*** (0.693)	1.630* (0.464)	1.714* (0.544)
Househusband/housewife	0.902 (0.079)	0.656*** (0.061)	0.820* (0.084)	0.792** (0.077)	1.560*** (0.137)	0.833* (0.082)	1.075 (0.097)	0.706*** (0.062)	0.635*** (0.076)
Education (reference: Low)									
Medium Educated	0.637*** (0.048)	0.810*** (0.061)	0.839** (0.067)	0.632*** (0.049)	0.489*** (0.037)	0.476*** (0.037)	0.711*** (0.055)	0.810*** (0.061)	0.608*** (0.051)
High Educated	0.212*** (0.016)	0.370*** (0.028)	0.394*** (0.032)	0.240*** (0.019)	0.184*** (0.014)	0.191*** (0.015)	0.310*** (0.024)	0.518*** (0.038)	0.274*** (0.024)
Trip Purpose (reference: work)									

	Jitney	Metro	BRT	Bus	Walking	Cycling	Taxi	Car	Moto
Health	0.324***	0.283***	0.332***	0.263***	0.150***	0.070***	1.116	0.392***	0.073***
	(0.047)	(0.043)	(0.057)	(0.045)	(0.022)	(0.018)	(0.165)	(0.056)	(0.027)
Leisure	0.281***	0.308***	0.316***	0.322***	0.456***	0.308***	0.752***	0.605***	0.320***
	(0.022)	(0.025)	(0.029)	(0.028)	(0.036)	(0.028)	(0.062)	(0.046)	(0.034)
Relationship with the head of household (reference: head)									
Partner	1.081	1.029	0.930	1.028	1.154*	1.145	1.087	0.953	0.862
	(0.079)	(0.078)	(0.077)	(0.082)	(0.085)	(0.095)	(0.083)	(0.070)	(0.085)
Son/Daughter	1.628***	1.620***	1.456***	1.456***	1.445***	1.307***	1.391***	0.740***	1.021
	(0.124)	(0.126)	(0.123)	(0.120)	(0.111)	(0.109)	(0.112)	(0.056)	(0.093)
Grandson/granddaughter	1.708***	1.641***	1.265	1.442**	1.443**	1.672***	1.491**	0.479***	0.835
	(0.274)	(0.269)	(0.225)	(0.251)	(0.232)	(0.294)	(0.251)	(0.078)	(0.172)
Trips on Saturday (Individual)	0.981	0.978	0.961	1.007	1.033	1.139***	0.985	1.153***	1.175***
	(0.027)	(0.028)	(0.030)	(0.030)	(0.029)	(0.034)	(0.028)	(0.032)	(0.039)
Trips on Weekday (Individual)	1.055**	1.023	1.013	1.078***	1.191***	1.318***	1.044	1.283***	1.380***
	(0.027)	(0.027)	(0.030)	(0.031)	(0.030)	(0.036)	(0.028)	(0.033)	(0.041)
Night Trip	0.467***	0.511***	0.552***	0.501***	0.294***	0.283***	0.676***	0.751***	0.515***
	(0.026)	(0.029)	(0.034)	(0.030)	(0.016)	(0.018)	(0.039)	(0.041)	(0.036)
Cars in household	0.624***	0.605***	0.663***	0.709***	0.606***	0.578***	0.665***	3.480***	0.508***
	(0.022)	(0.022)	(0.027)	(0.028)	(0.021)	(0.023)	(0.025)	(0.121)	(0.023)
Motorcycles in household	0.764***	0.869	0.797**	0.815**	0.795***	1.090	0.739***	0.837**	13.523***
	(0.067)	(0.079)	(0.081)	(0.078)	(0.070)	(0.102)	(0.069)	(0.073)	(1.213)
Travel time	1.025***	1.044***	1.033***	1.039***	0.924***	0.956***	0.973***	1.006***	0.969***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	423,870	423,870	423,870	423,870	423,870	423,870	423,870	423,870	423,870

Notes: Multinomial Model. Odds ratio, reduced version. For complete version see the appendix. P values were calculated with original estimates.
*** p<0.01, ** p<0.05, * <0.1. Standard errors in parentheses.
Chi Square for the full model: 498936.31***. Pseudo R2 for the full model: 0.34.

Source: Own elaboration based on 2017 household travel survey for Mexico City
Method: multinomial model

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6. Conclusions and policy implications

This research used two categorical models to explore how the built environment, individual variables, and trip characteristics influence ride-hailing adoption and the propensity of ride-hailing usage relative other transport alternatives. The rationale of the models builds on the conceptual framework presented in Figure 1, which incorporates the *Built Environment, Individual Mobility Demand, Purchasing Power,* and *Attitudinal Preferences,* as relevant dimensions influencing ride-hailing use. The framework puts special attention to *gender* and factors affecting *Personal Security* as considerations previously ignored in earlier research, even though given the nature of data used in the models we were not able to include variables connected to Personal Security. Our paper set out to test the applicability and relevance of previously identified factors influencing ride-hailing adoption in contexts outside of Latin America and Mexico. As such, findings from the previous section can be divided in those confirming results in previous research and those that suggest context-specific contributions to current academic debates.

On the one hand, our findings confirm that higher education and income have a positive effect on ride-hailing adoption, and that younger users are more likely to adopt TNC services. Such findings are well-aligned with existing research on ride-hailing in the academic literature (Alemi et al., 2018b; Dias et al., 2017; Tirachini, 2019). Our models support the hypothesis that ride-hailing adopters tend to be in their twenties and that the highest levels of education are associated with ride-hailing trips in Mexico City. In this context, wealthier populations who are more comfortable with new technologies, marking a divide between users and non-users along socioeconomic and demographic lines. We also found that ride-hailing is, at the time of the data collection (2017), a transport alternative to perform non-usual trips. This is reflected in the high estimates found in the logistic model for leisure and health trips with 3.808 and 9.908, respectively, which stands in contrasts with home trips (0.514), work trips (0.924 and non-significant), and study trips (0.560).

Built environment and public transit supply variables were also relevant to ride-hailing usage. The propensity to choose ride-hailing relative to other available modes decreases where there is a high level of transit supply. We also observe that areas characterized as having a higher degree of land-use diversity and population density, as measured by trip intensity, have higher levels of public transit usage However, in these zones, TNCs are preferred over walking and cycling. In addition, individuals living further away from the city center have a higher likelihood of using public transportation compared to ride-hailing, perhaps due to the longer distances and costs in ride-hailing that would be involved in trips in lower density areas of the city.

On the other hand, results about gendered factors deviate from what the international literature on ride-hailing suggests, pointing at gender and the influence of mobilities of care for the adoption and intensity of use of TNC services as relevant factors in contexts such as Mexico. As shown in section 2.2, research in LAC has pointed at gender as a significant determinant of travel patterns in cities in the region, with aspects associated with security, violence and crime affecting this group more visibly than others. Furthermore, emerging literature on mobilities of care support the hypothesis that gender (being female) is a relevant variable in ride-hailing adoption as tested in the logistic model. We find that women are 35% more likely to use ride-hailing modes compared to men. This result was also confirmed in the multinomial model comparing the relative odds of choosing other modes relative to ride-hailing for trips reporting in the reference week. Women were found to prefer ride-hailing to all other modes except for walking, where we did not find a significant effect. Moreover, cycling (relative to ride-hailing) had the lowest odds ratio estimate (0.183) for women. This finding is reinforced by the “househusband/housewife” category (occupation) that shows significant values and estimates in favor of ride-hailing relative to most alternative transport modes analyzed. The only exceptions were walking (estimate in the other direction) and cycling (not significant).

Findings related to gender suggest that individual motorized modes and taxis currently meet some of the complexities associated with the needs, perceptions, and vulnerabilities of women when moving in the city in different forms of transport. International literature on women's travel consistently demonstrates that women are more likely to trip chain, carry packages and accompany others during their trips, and make more stops and yet are less likely to have access to a private vehicle even if there is one in their household. In the Latam context they also experience high rates of harassment or fear of harassment in public transit, limiting times of day and contexts that they feel safe traveling in this mode. It is not surprising that women who can afford to access ride-hailing, a form of transport that offers flexibility for door-to-door on-demand trips, like that of a car and security features, prefer it over other modes. Security may be one of the main drivers for the high ratios observed in such modes for women. This suggests a potential for TNCs to adjust their operation and service patterns for women to increase perceptions of safety concerning other modes. They also point at preference in this group for individualized travel options under specific, non-usual, circumstances, which can open spaces for integration with public transit in areas and times of the day perceived as less safe.

The methodology followed in this paper shed light on the main characteristics affecting ride-hailing adoption as well as to establish some differences with other transport alternatives. Nevertheless, there are some limitations that should be addressed in further research and that are based mainly on the nature of the information used for the analysis: the Mexico City transport household survey from 2017. This study is limited by the fact that at the time of the survey, ride-hailing as a service was still consolidating and had much less diversification of services and market segmentation that is now being observed. Moreover, a transport household survey is an instrument used to understand commute patterns, but it is not specifically designed to study ride-hailing. As consequence, some key variables are not currently being considered. For example, it would be important to ask the mode commuters would have used should ride-hailing not being available for their last ride-hailing trip. As mentioned in the introduction, literature review and conceptual framework, the level of engagement with technology is a key factor in explaining ride-hailing usage. Future studies should find mechanisms to measure engagement with technology as well as other subjective variables reflecting perceptions of ride-hailing services.

Although we present a multinomial model, we did not move to a more elaborated discrete choice model such as mixed model or nested model given database limitations; namely reported trips in the survey, do not include set of scenarios where respondents are asked to select an option for a particular trip among different alternatives with different modes, costs, travel times, and other characteristics (as is the case in a discrete choice experiment). Further research in Mexico City could incorporate a discrete choice experiment and even evaluate integration with public transit.

A future line of research should focus on completely unpacking the connection between gender and ride-hailing. The coefficient estimates for gender in the logit and multinomial models shows an association, however we tested multiple interactions of gender with key variables (like stratum, education, household composition and trips purposes) without obtaining any statistically significant results, leaving the underlying mechanism of the effect unknown.

Challenges for policy concerning ride-hailing in contexts like Mexico are associated with the tension between opening spaces for modern travel alternatives that may serve a small portion of the demand and reducing transport-driven inequalities across the population. Findings in this paper point at potential entry points for the exploration of co-produced solutions between regulators, TNC providers, users, and incumbent operators in other modes. The infrequent nature of trips served by ride-hailing suggests a potential for multi-modality and changes in pricing and operation schemes that can better respond to the needs of the more vulnerable users. Positioning ride-hailing as a viable substitute for the private car and motorcycle can potentially contribute to reducing car dependency before reaching saturation levels.

Our models did not include attitudinal variables. However, we acknowledge that they can shed light on some of the issues. With the purpose of foster a more comprehensive research agenda in ride-hailing, we believe that future research should include this dimension and build on specific survey instruments that ask for peoples' perceptions such as fear of crime.

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Annex

Table A1. Influence of individual and trip-level characteristics on ride-hailing modal choice.

	Median	Mean	SD	Observations
Age	37	38.52	17.28	142415
Stratum	2	2.53	0.71	142415
Trips on Saturday (Individual)	2	1.29	1.09806	183677
Trips on Weekday (Individual)	2	2.012	0.98935	286516
Percentage Homebound Trips	0.5	0.4876	0.15758	87224
Percentage Work Trips	0.1667	0.2404	0.27757	107039
Percentage Study Trips	0	0.07479	0.17691	27258
Percentage Leisure Trips	0	0.07613	0.1701	36542
Percentage Health Trips	0	0.01355	0.07813	5662
Percentage Other Trips	0	0.1568	0.22566	80622
Night Trips	0	0.1611	0.2424	76160
Cars in household	0	0.5592	0.75646	54281
Motorcycles in household	0	0.06747	0.29437	54281
People in Home	4	3.714	1.66526	54281
Kids (under 5 years	0	0.2715	0.57441	54281
Elders (Above 65 years)	0	0.3144	0.61209	54281
Trips on Saturday (Home Level)	4	4.395	3.55324	625888
Weekday Trips (Home Level)	6	7.159	3.86954	1019571
Transit Intensity	0.3408	0.3481	0.0622	193
Trips Within District	0.3944	0.4054	0.12962	193
Distance to Center	16957	18741	20135.5	193

Observations for Age and Stratum are at the individual level (surveyed people).
Observations for variables related to trips are at the trip level.
Observations for variables related to the household are in household units.
Observations for Transit Intensity, Trips Within District, and Distance to Center are in district units.

Source: Own elaboration based on 2017 household travel survey for Mexico City

Table A2. Descriptive statistics by transport mode

	Transport Modes									
	TNC	**Jitney**	**Metro**	**BRT**	**Buses**	**Walk**	**Cycle**	**Taxi**	**Car**	**Moto**
Total Trips	2,166	111,724	34,898	7,766	11,298	133,937	10,200	16,850	90,155	4,876
Modal Share (%)	0.01	0.26	0.08	0.02	0.03	0.32	0.02	0.04	0.21	0.01
Trips By Day										
Saturday	1,095	40,768	12,498	2,699	4,183	48,933	4,186	7,964	40,525	1,940
(%)	0.51	0.36	0.36	0.35	0.37	0.37	0.41	0.47	0.45	0.40
Weekday	1,071	70,956	22,400	5,067	7,115	85,004	6,014	8,886	49,630	2,936
(%)	0.49	0.64	0.64	0.65	0.63	0.63	0.59	0.53	0.55	0.60
Schedule										
Day Trip	1,616	91,392	27,565	6,204	8,863	122,885	8,968	13,714	71,680	3,878
(%)	0.75	0.82	0.79	0.80	0.78	0.92	0.88	0.81	0.80	0.80
Night Trip	550	20332	7333	1562	2435	11052	1232	3136	18475	998
(%)	0.25	0.18	0.21	0.20	0.22	0.08	0.12	0.19	0.20	0.20
Stages										
One	1,986	21,660	1,434	688	1,375	131,184	10,062	14,128	87,138	4,823
(%)	0.92	0.19	0.04	0.09	0.12	0.98	0.99	0.84	0.97	0.99
Two	110	39,809	7,726	2,015	3,026	1,318	97	2,100	1,853	39
(%)	0.05	0.36	0.22	0.26	0.27	0.01	0.01	0.12	0.02	0.01
More Than Two	70	50255	25738	5063	6897	1435	41	622	1164	14
(%)	0.03	0.45	0.74	0.65	0.61	0.01	0.00	0.04	0.01	0.00
Stratum										
1 (Low)	2	1,238	199	31	46	1,547	116	57	301	48
(%)	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.01
2 (Medium-Low)	513	73,061	15,451	2,837	7,324	84,717	7,548	8,320	33,637	3,264
(%)	0.24	0.65	0.44	0.37	0.65	0.63	0.74	0.49	0.37	0.67
3 (Medium-High)	927	29,869	16,004	3,989	3,135	38,692	2,039	6,483	31,006	1,189

(%)	0.43	0.27	0.46	0.51	0.28	0.29	0.20	0.38	0.34	0.24
4 (High)	724	7,556	3,244	909	793	8,981	497	1,990	25,211	375
(%)	0.33	0.07	0.09	0.12	0.07	0.07	0.05	0.12	0.28	0.08
Age										
(10 - 15)	81	6118	733	248	453	14703	497	1061	4198	155
(%)	0.04	0.05	0.02	0.03	0.04	0.11	0.05	0.06	0.05	0.03
(15 - 20)	195	14162	3722	983	1198	10513	827	1201	4540	418
(%)	0.09	0.13	0.11	0.13	0.11	0.08	0.08	0.07	0.05	0.09
(20 - 30)	663	26607	9404	2077	2784	24030	2135	3065	14056	1774
(%)	0.31	0.24	0.27	0.27	0.25	0.18	0.21	0.18	0.16	0.36
(30 - 40)	493	21472	7091	1359	2166	25619	2152	2919	20601	1271
(%)	0.23	0.19	0.20	0.17	0.19	0.19	0.21	0.17	0.23	0.26
(40 - 50)	308	20089	6075	1273	2008	21853	2063	2997	20932	797
(%)	0.14	0.18	0.17	0.16	0.18	0.16	0.20	0.18	0.23	0.16
(50 - 60)	225	13934	4741	1066	1599	17849	1409	2511	14511	365
(%)	0.10	0.12	0.14	0.14	0.14	0.13	0.14	0.15	0.16	0.07
(>60)	201	9342	3132	760	1090	19370	1117	3096	11317	96
(%)	0.09	0.08	0.09	0.10	0.10	0.14	0.11	0.18	0.13	0.02
Education Level										
Low Education	390	55672	11347	2388	5239	85104	6436	8138	24735	2269
(%)	0.18	0.50	0.33	0.31	0.46	0.64	0.63	0.48	0.27	0.47
Middle Education	537	37857	12355	2786	3657	34767	2579	5342	24348	1607
(%)	0.25	0.34	0.35	0.36	0.32	0.26	0.25	0.32	0.27	0.33
High Education	1239	18195	11196	2592	2402	14066	1185	3370	41072	1000
(%)	0.57	0.16	0.32	0.33	0.21	0.11	0.12	0.20	0.46	0.21
Trip Purpose										
Work	403	31,319	11,396	2,242	3,496	15,150	3,162	2,387	20,901	1,553
(%)	0.19	0.28	0.33	0.29	0.31	0.11	0.31	0.14	0.23	0.32
Home	967	52,808	16,338	3,636	5,258	63,893	4,894	8,584	41,565	2,279

(%)	0.45	0.47	0.47	0.47	0.47	0.48	0.48	0.51	0.46	0.47
Study	106	8,268	2,378	634	810	6,949	285	650	2,995	182
(%)	0.05	0.07	0.07	0.08	0.07	0.05	0.03	0.04	0.03	0.04
Health	65	1,510	379	114	127	561	24	749	1,274	15
(%)	0.03	0.01	0.01	0.01	0.01	0.00	0.00	0.04	0.01	0.00
Leisure	423	6,035	1,932	528	723	7,314	582	1,870	10,471	293
(%)	0.20	0.05	0.06	0.07	0.06	0.05	0.06	0.11	0.12	0.06
Other	202	11,784	2,475	612	884	40,070	1,253	2,610	12,949	554
(%)	0.09	0.11	0.07	0.08	0.08	0.30	0.12	0.15	0.14	0.11

Source: Own elaboration based on 2017 household travel survey for Mexico City

Table A3. Influence of individual and trip-level characteristics on ride-hailing modal choice.

	Jitney	Metro	BRT	Bus	Walking	Cycling	Taxi	Car	Moto
Gender									
Male	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Female	0.950	0.784***	0.992	0.899*	0.973	0.208***	1.300***	0.553***	0.222***
	(0.053)	(0.045)	(0.062)	(0.054)	(0.055)	(0.013)	(0.077)	(0.031)	(0.017)
Age									
(10 to 15)	0.441***	0.308***	0.381***	0.399***	1.003	0.382***	0.806	1.823***	0.209***
	(0.068)	(0.049)	(0.066)	(0.066)	(0.154)	(0.065)	(0.129)	(0.281)	(0.041)
(15 to 20)	0.812**	0.786**	0.864	0.699***	0.910	0.699***	0.748***	0.890	0.509***
	(0.080)	(0.080)	(0.094)	(0.075)	(0.091)	(0.077)	(0.079)	(0.089)	(0.062)
(20 to 30)	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
(30 to 40)	1.163**	1.150**	0.970	1.113	1.211***	1.213***	1.282***	1.778***	0.931
	(0.077)	(0.079)	(0.074)	(0.082)	(0.081)	(0.090)	(0.091)	(0.118)	(0.074)
(40 to 50)	1.667***	1.509***	1.397***	1.513***	1.643***	1.765***	2.010***	2.455***	0.845*
	(0.133)	(0.124)	(0.125)	(0.131)	(0.132)	(0.154)	(0.169)	(0.196)	(0.081)
(50 to 60)	1.902***	1.888***	1.795***	1.972***	2.091***	1.997***	2.524***	2.335***	0.637***
	(0.172)	(0.174)	(0.180)	(0.192)	(0.190)	(0.196)	(0.238)	(0.211)	(0.073)
>60	1.865***	1.995***	1.732***	2.111***	2.359***	2.013***	2.809***	2.575***	0.232***
	(0.230)	(0.251)	(0.237)	(0.280)	(0.291)	(0.268)	(0.358)	(0.316)	(0.042)
Occupation									
Employed	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Had a Work but did not work	0.878	0.823	1.123	0.753	1.205	0.410***	1.238	0.845	0.930
	(0.244)	(0.237)	(0.350)	(0.232)	(0.335)	(0.134)	(0.357)	(0.234)	(0.321)
Unemployed - Looking for a job	2.401***	2.506***	2.178**	2.267***	2.980***	2.401***	2.380***	1.630*	1.714*
	(0.681)	(0.719)	(0.659)	(0.670)	(0.847)	(0.705)	(0.693)	(0.464)	(0.544)

Student	1.503***	1.552***	1.703***	1.743***	1.329***	0.986	1.095	1.008	0.953
	(0.138)	(0.147)	(0.175)	(0.176)	(0.123)	(0.106)	(0.109)	(0.093)	(0.116)
Househusband/housewife	0.902	0.656***	0.820*	0.792**	1.560***	0.833*	1.075	0.706***	0.635***
	(0.079)	(0.061)	(0.084)	(0.077)	(0.137)	(0.082)	(0.097)	(0.062)	(0.076)
Retired	0.927	0.821	0.904	0.729**	1.234*	0.644***	1.347**	0.836	0.621**
	(0.118)	(0.108)	(0.130)	(0.105)	(0.156)	(0.091)	(0.175)	(0.105)	(0.142)
Cannot work for life	0.462**	0.389**	0.543	0.706	1.141	0.406**	2.042*	0.970	0.004***
	(0.169)	(0.149)	(0.227)	(0.277)	(0.417)	(0.167)	(0.750)	(0.354)	(0.004)
Does not have a job	1.033	0.953	0.951	1.030	1.643***	1.127	1.409***	0.952	1.261
	(0.122)	(0.117)	(0.128)	(0.133)	(0.193)	(0.143)	(0.171)	(0.112)	(0.187)
Education									
Low Educated	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Medium Educated	0.637***	0.810***	0.839**	0.632***	0.489***	0.476***	0.711***	0.810***	0.608***
	(0.048)	(0.061)	(0.067)	(0.049)	(0.037)	(0.037)	(0.055)	(0.061)	(0.051)
High Educated	0.212***	0.370***	0.394***	0.240***	0.184***	0.191***	0.310***	0.518***	0.274***
	(0.016)	(0.028)	(0.032)	(0.019)	(0.014)	(0.015)	(0.024)	(0.038)	(0.024)
Trip Purpose									
Work	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Home	0.902	0.847**	0.838**	0.838**	1.475***	0.967	1.388***	0.962	0.887
	(0.060)	(0.058)	(0.062)	(0.060)	(0.099)	(0.069)	(0.098)	(0.064)	(0.070)
Study	1.078	1.156	1.179	1.186	0.940	0.572***	1.056	0.751**	0.738*
	(0.133)	(0.145)	(0.157)	(0.156)	(0.117)	(0.081)	(0.139)	(0.093)	(0.118)
Health	0.324***	0.283***	0.332***	0.263***	0.150***	0.070***	1.116	0.392***	0.073***
	(0.047)	(0.043)	(0.057)	(0.045)	(0.022)	(0.018)	(0.165)	(0.056)	(0.027)
Leisure	0.281***	0.308***	0.316***	0.322***	0.456***	0.308***	0.752***	0.605***	0.320***
	(0.022)	(0.025)	(0.029)	(0.028)	(0.036)	(0.028)	(0.062)	(0.046)	(0.034)
Other	1.033	0.864	0.834*	0.954	1.969***	0.753***	1.187*	1.201**	0.752***
	(0.096)	(0.082)	(0.087)	(0.096)	(0.182)	(0.074)	(0.115)	(0.111)	(0.083)

Relationship with the head of household									
Head	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Partner	1.081	1.029	0.930	1.028	1.154*	1.145	1.087	0.953	0.862
	(0.079)	(0.078)	(0.077)	(0.082)	(0.085)	(0.095)	(0.083)	(0.070)	(0.085)
Son/Daughter	1.628***	1.620***	1.456***	1.456***	1.445***	1.307***	1.391***	0.740***	1.021
	(0.124)	(0.126)	(0.123)	(0.120)	(0.111)	(0.109)	(0.112)	(0.056)	(0.093)
Grandson/granddaughter	1.708***	1.641***	1.265	1.442**	1.443**	1.672***	1.491**	0.479***	0.835
	(0.274)	(0.269)	(0.225)	(0.251)	(0.232)	(0.294)	(0.251)	(0.078)	(0.172)
Other	1.170*	1.223**	1.299**	1.009	1.138	1.060	1.104	0.530***	0.948
	(0.110)	(0.118)	(0.135)	(0.104)	(0.108)	(0.109)	(0.109)	(0.050)	(0.110)
No kinship	0.630***	0.737*	0.633**	0.676*	0.906	0.525***	0.596***	0.205***	0.556**
	(0.100)	(0.121)	(0.126)	(0.136)	(0.143)	(0.120)	(0.108)	(0.033)	(0.142)
Trips on Saturday (Individual)	0.981	0.978	0.961	1.007	1.033	1.139***	0.985	1.153***	1.175***
	(0.027)	(0.028)	(0.030)	(0.030)	(0.029)	(0.034)	(0.028)	(0.032)	(0.039)
Trips on Weekday (Individual)	1.055**	1.023	1.013	1.078***	1.191***	1.318***	1.044	1.283***	1.380***
	(0.027)	(0.027)	(0.030)	(0.031)	(0.030)	(0.036)	(0.028)	(0.033)	(0.041)
Night Trip	0.467***	0.511***	0.552***	0.501***	0.294***	0.283***	0.676***	0.751***	0.515***
	(0.026)	(0.029)	(0.034)	(0.030)	(0.016)	(0.018)	(0.039)	(0.041)	(0.036)
Stratum									
Stratum 1	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Stratum 2	0.654	0.306*	0.391	2.470	0.403	0.636	0.895	0.783	0.523
	(0.466)	(0.219)	(0.287)	(1.796)	(0.287)	(0.457)	(0.647)	(0.559)	(0.381)
Stratum 3	0.391	0.289*	0.376	1.362	0.232**	0.256*	0.681	0.564	0.262*
	(0.278)	(0.208)	(0.276)	(0.992)	(0.166)	(0.184)	(0.493)	(0.403)	(0.191)
Stratum 4	0.186**	0.130***	0.170**	0.612	0.120***	0.145***	0.403	0.435	0.129***
	(0.133)	(0.093)	(0.126)	(0.447)	(0.086)	(0.105)	(0.292)	(0.311)	(0.095)
Cars in household	0.624***	0.605***	0.663***	0.709***	0.606***	0.578***	0.665***	3.480***	0.508***
	(0.022)	(0.022)	(0.027)	(0.028)	(0.021)	(0.023)	(0.025)	(0.121)	(0.023)

Motorcycles in household	0.764***	0.869	0.797**	0.815**	0.795***	1.090	0.739***	0.837**	13.523***
	(0.067)	(0.079)	(0.081)	(0.078)	(0.070)	(0.102)	(0.069)	(0.073)	(1.213)
Kids (under 5 years)	1.035	0.947	1.007	0.973	1.089*	1.057	1.179***	1.076	1.018
	(0.049)	(0.046)	(0.053)	(0.049)	(0.052)	(0.053)	(0.058)	(0.051)	(0.056)
Elders (Above 65 years)	1.100	1.082	1.175**	1.226***	1.149**	1.201***	1.257***	1.062	1.200**
	(0.073)	(0.073)	(0.084)	(0.086)	(0.076)	(0.084)	(0.086)	(0.070)	(0.095)
Trips in Weekday (Home Level)	1.042***	1.039***	1.040***	1.035***	1.040***	1.032***	1.020**	1.003	1.016
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.011)
Trips on Saturday (Home Level)	0.979**	0.985	0.978**	0.984	0.969***	0.984	1.010	0.986	0.941***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.012)
Transit Intensity									
Low	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Medium	0.855	1.105	0.630***	1.174	1.541***	1.533***	1.426***	1.186	2.108***
	(0.109)	(0.145)	(0.090)	(0.159)	(0.199)	(0.215)	(0.192)	(0.151)	(0.327)
Medium/High	1.117	0.716***	0.785*	1.179	1.549***	1.465***	1.613***	1.150	2.138***
	(0.137)	(0.090)	(0.109)	(0.154)	(0.194)	(0.209)	(0.212)	(0.141)	(0.335)
High	1.004	0.692***	0.631***	0.843	1.239*	1.005	1.683***	1.116	1.833***
	(0.121)	(0.086)	(0.086)	(0.109)	(0.152)	(0.145)	(0.218)	(0.134)	(0.290)
Transit Intensity (Origin)									
Low	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Medium	1.172	1.151	1.378**	0.886	0.758**	0.697***	0.836	0.841	0.637***
	(0.129)	(0.133)	(0.172)	(0.105)	(0.084)	(0.083)	(0.096)	(0.093)	(0.083)
Medium/High	1.108	1.238**	0.782**	1.157	0.818*	0.566***	0.819*	0.873	0.564***
	(0.115)	(0.134)	(0.093)	(0.129)	(0.086)	(0.067)	(0.090)	(0.090)	(0.073)
High	1.455***	2.328***	1.431***	1.419***	1.078	0.777**	0.912	0.977	0.733**
	(0.150)	(0.249)	(0.168)	(0.157)	(0.113)	(0.094)	(0.100)	(0.100)	(0.096)
Transit Intensity (Destination)									
Low	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference

Medium	1.195*	1.139	1.400***	0.869	0.778**	0.740***	0.848	0.863	0.634***
	(0.127)	(0.127)	(0.168)	(0.099)	(0.083)	(0.085)	(0.095)	(0.092)	(0.080)
Medium/High	1.148	1.261**	0.758**	1.102	0.828*	0.586***	0.888	0.897	0.592***
	(0.115)	(0.131)	(0.087)	(0.118)	(0.084)	(0.067)	(0.094)	(0.089)	(0.074)
High	1.381***	2.108***	1.283**	1.188	0.989	0.728***	0.889	0.903	0.658***
	(0.136)	(0.217)	(0.145)	(0.126)	(0.100)	(0.084)	(0.094)	(0.089)	(0.083)
Trips Within District									
Low	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Medium	1.241**	1.461***	1.448***	1.296**	0.588***	0.799*	1.253**	1.269**	1.553***
	(0.118)	(0.141)	(0.150)	(0.134)	(0.057)	(0.095)	(0.127)	(0.120)	(0.204)
Medium/High	1.890***	4.488***	2.260***	1.730***	0.893	1.371**	2.269***	2.158***	4.212***
	(0.246)	(0.597)	(0.323)	(0.242)	(0.118)	(0.210)	(0.313)	(0.281)	(0.703)
High	1.112	2.038***	0.390***	1.072	0.409***	0.554***	1.007	1.063	1.881***
	(0.206)	(0.389)	(0.080)	(0.209)	(0.077)	(0.115)	(0.196)	(0.197)	(0.419)
Trips Within District (Origin)									
Low	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Medium	1.399***	0.864*	0.956	1.410***	2.049***	1.611***	1.326***	1.307***	1.028
	(0.115)	(0.073)	(0.086)	(0.125)	(0.171)	(0.161)	(0.115)	(0.107)	(0.111)
Medium/High	1.128	0.754**	0.798*	1.071	1.814***	1.669***	1.095	1.003	0.674***
	(0.121)	(0.084)	(0.096)	(0.124)	(0.198)	(0.207)	(0.124)	(0.108)	(0.091)
High	1.423**	1.294	1.411*	1.585***	2.864***	2.394***	1.498**	1.403**	1.035
	(0.225)	(0.214)	(0.250)	(0.264)	(0.458)	(0.417)	(0.247)	(0.223)	(0.192)
Trips Within District (Destination)									
Low	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Medium	1.312***	0.794***	0.943	1.297***	1.918***	1.495***	1.139	1.162*	0.992
	(0.104)	(0.064)	(0.082)	(0.111)	(0.155)	(0.144)	(0.096)	(0.092)	(0.104)
Medium/High	1.082	0.720***	0.800*	0.945	1.701***	1.558***	0.943	0.905	0.628***

	(0.112)	(0.077)	(0.092)	(0.105)	(0.178)	(0.186)	(0.103)	(0.093)	(0.082)
High	1.365**	1.237	1.415**	1.405**	2.700***	2.230***	1.495**	1.268	0.960
	(0.207)	(0.197)	(0.241)	(0.225)	(0.415)	(0.374)	(0.238)	(0.193)	(0.172)
Distance to Centre									
First Ring	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Second Ring	1.204*	0.949	0.590***	0.583***	0.799**	0.656***	1.317**	0.950	1.180
	(0.128)	(0.102)	(0.070)	(0.067)	(0.088)	(0.091)	(0.152)	(0.101)	(0.179)
Third Ring	1.433***	0.563***	0.592***	0.743**	0.556***	0.438***	1.225	0.854	1.590**
	(0.194)	(0.078)	(0.087)	(0.107)	(0.078)	(0.076)	(0.181)	(0.115)	(0.294)
Fourth Ring	2.780***	1.171	1.784**	2.520***	0.914	0.632*	2.233***	1.693**	3.432***
	(0.643)	(0.279)	(0.453)	(0.601)	(0.216)	(0.167)	(0.547)	(0.392)	(0.965)
Distance to Centre (Origin)									
First Ring	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Second Ring	1.544***	0.568***	0.461***	1.032	1.331***	1.089	1.123	1.233**	0.912
	(0.134)	(0.050)	(0.046)	(0.097)	(0.119)	(0.121)	(0.105)	(0.107)	(0.111)
Third Ring	1.391***	0.396***	0.928	0.937	1.472***	1.506***	1.026	1.247**	0.878
	(0.155)	(0.046)	(0.113)	(0.111)	(0.170)	(0.209)	(0.123)	(0.139)	(0.131)
Fourth Ring	2.044***	0.210***	0.325***	1.364	2.159***	2.669***	1.277	1.747***	1.233
	(0.396)	(0.043)	(0.071)	(0.273)	(0.426)	(0.581)	(0.260)	(0.339)	(0.284)
Distance to Centre (Destination)									
First Ring	reference	reference	reference	reference	reference	reference	reference	reference	reference
	reference	reference	reference	reference	reference	reference	reference	reference	reference
Second Ring	1.572***	0.539***	0.462***	1.057	1.357***	1.125	1.045	1.280***	1.000
	(0.131)	(0.046)	(0.044)	(0.095)	(0.117)	(0.120)	(0.095)	(0.107)	(0.118)
Third Ring	1.525***	0.399***	0.930	0.987	1.670***	1.679***	1.179	1.443***	1.088
	(0.163)	(0.044)	(0.109)	(0.112)	(0.185)	(0.224)	(0.137)	(0.154)	(0.156)
Fourth Ring	1.699***	0.155***	0.243***	1.158	1.802***	2.273***	1.040	1.593***	1.166
	(0.300)	(0.029)	(0.049)	(0.212)	(0.326)	(0.456)	(0.195)	(0.281)	(0.249)
Travel time	1.025***	1.044***	1.033***	1.039***	0.924***	0.956***	0.973***	1.006***	0.969***

	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female * Elders (Above 65 years)	0.807***	0.812***	0.839**	0.760***	0.789***	0.499***	0.820**	0.991	0.778**
	(0.061)	(0.063)	(0.070)	(0.062)	(0.060)	(0.046)	(0.065)	(0.075)	(0.089)
Constant	12.341***	9.736***	7.488***	0.394	454.357***	62.019***	8.015***	6.997***	18.544***
	(8.961)	(7.128)	(5.636)	(0.293)	(330.118)	(45.563)	(5.923)	(5.094)	(13.882)
Observations	423,870	423,870	423,870	423,870	423,870	423,870	423,870	423,870	423,870

Notes: Multinomial Model. Odds ratio, reduced version. For complete version see the appendix. P values were calculated with original estimates.
*** p<0.01, ** p<0.05, * <0.1. Standard errors in parentheses
Chi Square for the full model: 498936.31***. Pseudo R2 for the full model: 0.34.
Data source: 2017 household travel survey for Mexico City