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# Optimal prices for ridesourcing in the presence of taxi, public transport and car competition

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ABSTRACT

Ridesourcing platforms have acquired an important role as an alternative travel mode in almost all major cities in the world. These new mobility applications offer benefits for users over traditional taxi and public transport alternatives. However, there is mounting evidence that ridesourcing worsens traffic congestion. Given this potential negative impact and the complicated relationship between travel modes, it is unclear how policymakers should respond to the appearance of this new transport option. In this paper, we present a social welfare maximization model with four modes (automobile, taxi, buses and ridesourcing services) to derive the optimal first-best and second-best fares, considering the congestion externality generated by each mode. We apply this model to Santiago, Chile, using available parameter estimates to derive optimal fares with a novel inverse demand system (Inverse Product Differentiation Logit model). The results indicate that ridesourcing fares should be 29% higher per ride in the first-best scenario and 59% higher in the second-best scenario compared to current levels. However, our second-best scenario (in which buses and taxis have fares given by current levels and there is no congestion pricing for cars) reaches only 18% of the welfare gains from a first-best scenario. Sensitivity analysis shows that these results are not sensitive to several key assumptions, however they are sensitive to the parametrization of the flow-delay function in the second-best scenario. Our simulations also show that the optimal surcharge should be slightly higher if the average occupancy rate for ridesourcing services increases. This result is due to the higher overall use of this service, as the average fare per passenger decreases when more passengers ride together.

## 1. Introduction

Ridesourcing applications are now a standard mobility option in major cities of the world. Companies such as Uber, Lyft, Cabify, Ola, Didi Chuxing and others have seen extraordinary growth during the past few years. Since its creation in 2012, Didi has become the largest ridesourcing company, with over 450 million users, 21 million drivers and over 30 million trips per day (Tirachini, 2020). Uber, one of the oldest and best-known applications, is present in over 800 cities, and in many of these cities, Uber, together with other applications, has surpassed formal taxis as an on-demand point-to-point mobility service (SFCTA, 2017; Tirachini, 2020). This explosive growth is explained by the desirable attributes these services provide to users compared to traditional transport modes. Ease

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of payment, the convenience of using a smartphone application to procure a ride, low wait times, comfort and security are among the main reasons users cite for preferring these services, particularly for social events.[1]

Despite their growing popularity, ridesourcing applications also have the potential to generate or exacerbate existing negative externalities. One of the main concerns is the effect that these platforms may have on the number of vehicle-kilometres travelled (VKT) and their consequent impact on congestion and other traffic-related externalities. Empirical studies show that ridesourcing increases VKT (Henao and Marshall, 2019; Tirachini and Gomez-Lobo, 2020) and traffic delays in cities (Agarwal et al., 2019; Erhardt et al., 2019; Tarduno, 2021). While existing studies do not provide a consensus on the mechanisms driving empirical estimates of the impact of ridesourcing on traffic slowdowns, these estimates likely reflect a combination of induced trips, deadheading (empty kilometers between the end of one ride and the beginning of the next one) and substitution away from public transport (Erhardt et al., 2019; Henao and Marshall, 2019; Tirachini, 2020). These negative effects are not offset by the positive impacts of ridesourcing services on congestion unless passenger occupancy rates per trip are much higher than current levels (Tirachini and Gomez-Lobo, 2020).

In principle, ridesourcing can be both a complement to and a substitute for public transport. However, recent empirical studies show that the substitution effect is larger than the complementarity effect. In Santiago, Tirachini and del Río (2019) report that for every ridesourcing user who makes a trip in combination with public transport, there are eleven ridesourcing users who replace public transport trips. In New Delhi, Agarwal et al. (2019) show that Metro ridership increased by 2.4% on days on which there were no ridesourcing services available due to drivers' strikes, and Erhardt et al. (2021) estimate a 10% reduction in public transport demand in San Francisco due to ridesourcing use. Pooling several US cities together, Ward et al. (2021) have recently estimated that ridesourcing increases vehicle registrations in the United States and that, in general, there are no effects on public transport ridership; however, reductions in ridership do seem to have occurred in areas with higher incomes and childless households.

Understanding the relationship between ridesourcing platforms, public transport and traffic congestion has significant policy implications. The perceived increase in VKT due to the proliferation of ridesourcing trips is usually put forward by city or transport authorities as a justification to impose a price and/or quantity control on these services. Some examples of current charges for ridesourcing services are the following: Chicago ($0.40 per ride; California (0.3% of revenues); Sao Paulo, Brazil (R$0.10 base charge per kilometre, R: Brazilian real); Mexico City (1.5% of trip fare) and Porto Alegre, Brazil (R$73 per vehicle per month). The scheme in Sao Paulo, Brazil, introduced in 2016, is interesting given that there is a base charge (R$0.10 per kilometre) but the regulator can increase this charge if road infrastructure is congested, and can decrease it in areas outside the city centre, in off-peak periods, if the vehicle is environmentally friendly or if the driver is a woman (Alonso Ferreira et al., 2018).

In this paper, we investigate the issues of ridesourcing, public transport and congestion by presenting a social welfare maximization model with four modes (automobiles, taxis, buses and ridesourcing services) to derive the optimal first-best and second-best fares, considering the congestion externality generated by each mode. We empirically apply our model to the case of Santiago, Chile, to obtain numerical results for the optimal pricing of all modes (first-best fares) or just the ridesourcing service (second-best fares). Our paper can inform policy discussions surrounding the optimal charges of ridesourcing services and, if applied to other cities, could provide quantitative guidance to evaluate the charging schemes presented above or similar initiatives in other cities.

There is an extensive literature in economics and engineering that attempts to characterize optimal prices in urban transport systems. Road pricing of automobiles is the most common topic in this literature, followed by public transport pricing. In the case of buses and trains, a usual result from social welfare maximisation models is that public transport should be subsidised either on first-best grounds (due to economies of scale) or on second-best grounds (if there is congestion and there is no road pricing for cars, as shown by Else (1985), Parry and Small (2009) and Basso and Silva (2014), among others). This literature has been extended to the optimal pricing of taxis, in which a known result is that in the absence of congestion, taxis should be subsidised, given the existence of economies of scale in users' waiting time (Arnott, 1996). However, this result may not hold in the presence of congestion (Yang et al., 2005). With the advent of ridesourcing services and e-hailing platforms for taxis, the study of pricing strategies for these new modal alternatives has also emerged, either through the development of one-mode models (ridesourcing only, as in Zha et al., 2016) or through the inclusion of competition between e-hailing and street-haling in the taxi industry (Wang et al., 2016; He et al., 2018). Decision variables include the optimal fare, the commission paid to drivers, and in some cases the structure of dynamic or surge pricing (for a review, see Wang and Yang, 2019).

Particularly relevant to our study is the contribution of Gomez-Gelvez (2021), who, using data from Bogotá, Colombia, estimates the optimal congestion tax for a monopoly ridesourcing platform as 12% of the fare in the morning peak period. This paper uses a model with waiting time and fares that are endogenously determined. A limitation of this paper, however, is that there is only one outside option for users.

Our work extends the previous literature in three relevant ways. First, we formulate and solve a four-mode problem, in which a social welfare maximisation model is developed to find the optimal price of private cars, taxis, ridesourcing and public transport services. Even though the actual application of the model is performed assuming four modes, the framework is general enough to accommodate any number of modes. The model is then solved for a second-best scenario in which only the ridesourcing fare can be optimized, while the car, taxi and public transport fares are exogenously fixed. Analytically, our model is an extension of four modes of the two-mode problem (car and public transport) presented by Small and Verhoef (2007) and of the three-mode problem (car, public transport and a non-motorised mode) presented by Tirachini and Hensher (2012).

Second, we add to the literature on ridesourcing pricing by analysing optimal first-best and second-best ridesourcing fares in a

[1] See Tirachini (2020) for a review of seven studies in which users are asked their reasons for using a ridesourcing application.

framework in which ridesourcing competes for patronage with cars, taxis and public transport. In our model, intermodal interactions are accounted for in the analysis of optimal ridesourcing fares, as all modes can cause traffic externalities and there is cross-congestion between modes. The setting of a four-mode framework is important from a sustainability point of view, since the effects of the growth of ridesourcing services are different depending on whether demand comes mostly from other low-occupancy modes (such as taxis and private cars) or from public transport.

Third, we use a state-of-the-art inverse demand system for the operationalization of the model, which is tractable, yet flexible enough to accommodate arbitrary substitution relationships among the different modes in our study. Furthermore, the model does not require arbitrary assumptions regarding hierarchical nesting structures among goods, as in the nested logit model. We use the Indirect Product Differentiation Logit (IPDL) demand model recently proposed by Fosgerau et al. (2021). We calibrate this model using data from the city of Santiago, Chile, to gauge the effects of different mode externalities on optimal fares and to compare these to current fare levels. To the best of our knowledge, this is the first use of this model in a transport-related context, and an improvement over previous work using calibrated inverse demand models, such as Ahn (2009), to determine optimal fares for multimodal transport systems.

The results of the paper show that in a first-best scenario, where automobiles and taxis can be charged a congestion tax and buses can be subsidized, there is an optimal 29.4% surcharge on ridesourcing services to internalize the congestion externality generated by this mode. In a second-best scenario where the only available policy instrument is a charge on ridesourcing services, the optimal charge for this mode increases to 58.8%. However, the welfare gains of the second-best scenario are only 17.8% of the welfare gains from applying first-best prices. Thus, there is much to gain from policy instruments that can optimally change prices for all modes.

We test the sensitivity of our results to changes in our initial demand assumptions for the ridesourcing mode and find only minor changes in our results. We also analyse the effects of changes in the parametrization of the BPR (*Bureau of Public Roads*) function that we use to model the impact of traffic flows on travel times. The first-best results do not change significantly. However, the second-best results are sensitive to the parametrization of this function, since overall congestion is higher in this scenario, and given the non-linear nature of this function, optimal fare will be more sensitive to the impact of traffic flows on travel times.

Finally, we also explore the effects of increasing the occupancy rates of the ridesourcing mode on optimal first-best and second-best fares. Interestingly, the optimal first-best and second-best surcharges are proportionally higher as the occupancy rate increases. The reason is that, while a higher occupancy rate does lower the per passenger congestion externality, it also lowers the per passenger fare, incentivising the use of this mode. This second effect is more important in our application, and calls for an increase in the optimal surcharge per trip (although not in the per passenger charge) as the average occupancy rate increases.

The rest of the paper is organized as follows. In the next section, we present our model with four transport modes and derive the optimal fare formulas, assuming a first-best scenario in which each mode can be taxed optimally and then a second-best scenario in which only the ridesourcing service can be optimally taxed. We then present the IPDL inverse demand system and explain the advantages of using this model over the available alternatives. We follow this by applying the model to Santiago, Chile, using estimated parameters from this city as well as parameters from the literature. The paper concludes with a discussion of the results and possible avenues for further research in this area.

## 2. Multimodal optimal pricing model

This section presents the model and the welfare maximization under two scenarios: first-best fares and second-best fares when only the ridesourcing applications can be charged a tax. We extend the two-mode model presented by Small and Verhoef (2007, Chapter 4) and the three mode model developed by Tirachini and Hensher (2012) to four modes: private car, bus, taxi and ridesourcing. The demand (number of trips) for each of these modes is denoted as $q_a$, $q_b$, $q_e$ and $q_r$, respectively.

As is standard in this literature, we assume a total benefit function $B(q_a,q_b,q_e,q_r)$ that represents the total surplus of a representative consumer for a vector of aggregate rides in each mode. This benefit function can be derived from a quasi-linear utility function of a representative consumer (see Arnott and Yan, 2000 for details). Assuming quasi-linearity implies changes in the price of each mode have no income effects on the demand for rides. If the expenditure share of transport is low and/or the income elasticity of demand for transport services is small, then this is not an unreasonable assumption.

A brief explanation of the representative consumer modelling approach is in order. This is a modelling technique used in economics whereby the aggregate behavior of heterogenous economic agents can be described as the result of decisions made by an 'average', 'typical' or 'representative' consumer. In the case of discrete choice models, the aggregate behavior of diverse individuals choosing among different options is equivalent to the choices made by a representative consumer with preferences for diversity. For example, Anderson et al. (1988) show that a logit model for market shares can be modeled as if generated by a representative consumer with a particular quasi-linear utility function who values consuming a diverse basket of the goods on offer. Fosgerau and De Palma (2016) extend this result and show that the demands of any additive random utility model can be derived from a representative consumer model with taste for diversity. Therefore, the assumption of representative consumer for the present context is not restrictive. See also the discussion of the IDPL model in Section 3.

The partial derivative of the total benefit function gives the inverse demand (willingness to pay) for an additional ride in each mode:[2]

[2] $p_k(q_a, q_b, q_e, q_r)$ is the willingness to pay for an additional ride as a function of total trips in each mode, which is the inverse of a direct demand function. We use inverse demand functions in our application as it is easier to derive first-best and second-best prices from them.

$$p_k(q_a, q_b, q_e, q_r) = \frac{\partial B}{\partial q_k}(q_a, q_b, q_e, q_r),\ k = \{a, b, e, r\} \tag{1}$$

We also define $C_k$ as the total cost for mode $k$, and $c_k$ as the average cost of mode $k$. Therefore, for each mode $C_k = q_k \bullet c_k$. In addition, the average cost of each mode is composed of user related average cost $cu_k$ (access time, waiting time, in-vehicle time) and operator related average cost $co_k$ (fuel or energy consumption, maintenance, driver wages, etc.). Therefore, for each mode, $c_k = cu_k + co_k$.

Individuals choose the number of trips in each mode, so that the willingness to pay for the last ride equals the perceived cost in each mode. In other words:

$$\frac{\partial B}{\partial q_a}(q_a, q_b, q_e, q_r) = c_a + \tau_a \tag{2}$$

$$\frac{\partial B}{\partial q_j}(q_a, q_b, q_e, q_r) = cu_j + \tau_j,\ j = \{b, e, r\} \tag{3}$$

where $\tau_a$ is a tax (e.g. congestion charge) applied to private automobiles, while $\tau_j$ is the fare in each of the three other modes. The only difference between these first-order conditions is that in the case of private cars, the user pays not only their time and the tax but also the direct operational cost of their trip. In the other modes, passengers only pay the fare and their time costs. Since fares fund operators, users in these other modes pay for operational costs indirectly, but fares could exhibit a positive margin over costs (e.g. due to high regulated fares in the case of taxis or market power in the case of ride-sourcing) or a negative margin (e.g. due to subsidies in the case of public transport).

### 2.1. First-best tariffs

First-best prices are obtained by maximizing total welfare:

$$\max_{q_a, q_b, q_e, q_r} W = B(q_a, q_b, q_e, q_r) - q_a \bullet c_a - q_b \bullet c_b - q_e \bullet c_e - q_r \bullet c_r \tag{4}$$

We assume that there is sufficient capacity for each mode, so we do not include capacity constraints in the above problem. We justify this assumption further below when discussing the application for Santiago. When maximizing the welfare function (4) with respect to each $q_j$, it is straightforward to show, using (2) and (3), that optimal first best fares are given by:

$$\tau_a^{FB} = q_a \bullet \frac{\partial c_a}{\partial q_a} + q_b \bullet \frac{\partial c_b}{\partial q_a} + q_e \bullet \frac{\partial c_e}{\partial q_a} + q_r \bullet \frac{\partial c_r}{\partial q_a} \tag{5.a}$$

$$\tau_b^{FB} = co_b + q_a \bullet \frac{\partial c_a}{\partial q_b} + q_b \bullet \frac{\partial c_b}{\partial q_b} + q_e \bullet \frac{\partial c_e}{\partial q_b} + q_r \bullet \frac{\partial c_r}{\partial q_b} \tag{5.b}$$

$$\tau_e^{FB} = co_e + q_a \bullet \frac{\partial c_a}{\partial q_e} + q_b \bullet \frac{\partial c_b}{\partial q_e} + q_e \bullet \frac{\partial c_e}{\partial q_e} + q_r \bullet \frac{\partial c_r}{\partial q_e} \tag{5.c}$$

$$\tau_r^{FB} = co_r + q_a \bullet \frac{\partial c_a}{\partial q_r} + q_b \bullet \frac{\partial c_b}{\partial q_r} + q_e \bullet \frac{\partial c_e}{\partial q_r} + q_r \bullet \frac{\partial c_r}{\partial q_r} \tag{5.d}$$

To understand these conditions, note that total costs are given by:

$$C(q_a, q_b, q_e, q_r) = q_a \bullet c_a + q_b \bullet c_b + q_e \bullet c_e + q_r \bullet c_r$$

So that the marginal cost of an additional trip in automobile is:

$$mc_a = c_a + q_a \bullet \frac{\partial c_a}{\partial q_a} + q_b \bullet \frac{\partial c_b}{\partial q_a} + q_e \bullet \frac{\partial c_e}{\partial q_a} + q_r \bullet \frac{\partial c_r}{\partial q_a} = c_a + mec_a \tag{6}$$

where we define $mec_a$ as the marginal external cost on all modes of an additional automobile ride. Since automobile users already face the total average cost of using this mode (see Eq. (2)), the optimal tax only includes the last four terms of the right-hand side (RHS) of Eq. (6). These terms measure the externality (in travel times and operating costs) that the additional automobile trip generates in users of automobiles and other modes ($mec_a$).

For the other modes, the marginal social cost is given by:

$$mc_k = cu_k + co_k + q_a \bullet \frac{\partial c_a}{\partial q_k} + q_b \bullet \frac{\partial c_b}{\partial q_k} + q_e \bullet \frac{\partial c_e}{\partial q_k} + q_r \bullet \frac{\partial c_r}{\partial q_k} = cu_k + co_k + mec_k,\ k = \{b, e, r\} \tag{7}$$

Since users pay for their average time costs (see Eq. (3)), the optimal fare for these other modes includes the average operating costs plus the externality generated in the own mode and other modes ($co_k + mec_k$) by an additional ride.

In all modes, the externality includes the congestion (time) effect plus any impact on the operating costs of each mode, including those of the own mode:

$$q_k \bullet \frac{\partial c_k}{\partial q_j} = q_k \bullet \frac{\partial cu_k}{\partial q_j} + q_k \bullet \frac{\partial co_k}{\partial q_j}, \ j,k = \{a,b,e,r\} \tag{8}$$

### 2.2. Second-best tariffs

We now assume that there is no congestion charge for automobiles, and that fares for buses and taxis are fixed parameters, $\tilde{\tau}_b$ and $\tilde{\tau}_e$, exogenously defined. This assumption is realistic for most cities, where taxi fares and bus fares are regulated (perhaps not at their optimal level) and there is no congestion charging. We assume that the only policy variable is the fare of the ridesourcing application. In this case, welfare maximization is given by the following optimization problem:

$$\max_{q_r} W = B(q_a, q_b, q_e, q_r) - q_a \bullet c_a - q_b \bullet c_b - q_e \bullet c_e - q_r \bullet c_r \tag{9}$$

Subject to:

$$\frac{\partial B}{\partial q_a}(q_a, q_b, q_e, q_r) = c_a \tag{10.a}$$

$$\frac{\partial B}{\partial q_b}(q_a, q_b, q_e, q_r) = cu_b + \tilde{\tau}_b \tag{10.b}$$

$$\frac{\partial B}{\partial q_e}(q_a, q_b, q_e, q_r) = cu_e + \tilde{\tau}_e \tag{10.c}$$

$$\frac{\partial B}{\partial q_r}(q_a, q_b, q_e, q_r) = cu_r + \tau_r \tag{10.d}$$

To solve the maximization problem, we define the Lagrange function (11) with the corresponding Lagrange multipliers $\gamma_a, \gamma_b, \gamma_e$ and $\gamma_r$ for each of the constraints (10a)–(10d):

$$L = B(q_a, q_b, q_e, q_r) - q_a \bullet c_a - q_b \bullet c_b - q_e \bullet c_e - q_r \bullet c_r + \gamma_a \bullet \left(\frac{\partial B}{\partial q_a} - c_a\right) + \gamma_b \bullet \left(\frac{\partial B}{\partial q_b} - cu_b - \tilde{\tau}_b\right) + \gamma_e \bullet \left(\frac{\partial B}{\partial q_e} - cu_e - \tilde{\tau}_e\right) + \gamma_r \bullet \left(\frac{\partial B}{\partial q_r} - cu_r - \tau_r\right) \tag{11}$$

The first-order conditions for Eq. (11) are shown in the Appendix. Using the notation $\frac{\partial^2 B}{\partial q_k \partial q_j} = B_{kj}$ and $\frac{\partial c_k}{\partial q_j} = c_{kj}$, and after some algebraic work, we obtain the following optimality conditions:

$$\gamma_a \bullet (B_{aa} - c_{aa}) + \gamma_b \bullet (B_{ba} - cu_{ba}) + \gamma_e \bullet (B_{ea} - cu_{ea}) = mec_a \tag{12a}$$

$$\gamma_a \bullet (B_{ab} - c_{ab}) + \gamma_b \bullet (B_{bb} - cu_{bb}) + \gamma_e \bullet (B_{eb} - cu_{eb}) = co_b + mec_b - \tilde{\tau}_b \tag{12b}$$

$$\gamma_a \bullet (B_{ae} - c_{ae}) + \gamma_b \bullet (B_{be} - cu_{be}) + \gamma_e \bullet (B_{ee} - cu_{ee}) = co_e + mec_e - \tilde{\tau}_e \tag{12c}$$

$$\gamma_a \bullet (B_{ar} - c_{ar}) + \gamma_b \bullet (B_{br} - cu_{br}) + \gamma_e \bullet (B_{er} - cu_{er}) = co_r + mec_r - \tau_r \tag{12d}$$

From the first three Eqs. (12a)–(12c), we can solve for the Lagrange multipliers. Using matrix notation, these are:

$$G = \begin{bmatrix} \gamma_a \\ \gamma_b \\ \gamma_e \end{bmatrix} = A^{-1} \bullet E \tag{13}$$

where $A = \begin{bmatrix} (B_{aa} - c_{aa}) & (B_{ba} - cu_{ba}) & (B_{ea} - cu_{ea}) \\ (B_{ab} - c_{ab}) & (B_{bb} - cu_{bb}) & (B_{eb} - cu_{eb}) \\ (B_{ae} - c_{ae}) & (B_{be} - cu_{be}) & (B_{ee} - cu_{ee}) \end{bmatrix}$ and $E = \begin{bmatrix} mec_a \\ co_b + mec_b - \tilde{\tau}_b \\ co_e + mec_e - \tilde{\tau}_e \end{bmatrix}$

With these results, the optimal second-best tariff for the ridesourcing service derived from Eq. (12d) is:

$$\tau_r = co_r + mec_r - \left(A^{-1} \bullet E\right)^{\mathsf{T}} \bullet B \tag{14}$$

where $B = \begin{bmatrix} (B_{ar} - c_{ar}) \\ (B_{br} - cu_{br}) \\ (B_{er} - cu_{er}) \end{bmatrix}$

Now we need to show that the last matrix term in (14) involves the diversion ratios of each mode. The diversion ratios measure the change in the number of rides in one mode as the number of rides increases in another mode or $\frac{dq_k}{dq_j}$ for modes $k$, $j$.[3]

To do this, we take the total differentiation of restrictions (10.a)–(10.c) with respect to the number of trips in each mode. The change in the number of trips must be such that these restrictions are always met. The results are:

$$dq_a\bullet(\mathrm{B_{aa}} - \mathrm{c_{aa}}) + \mathrm{dq_b}\bullet(\mathrm{B_{ab}} - \mathrm{c_{ab}}) + \mathrm{dq_e}\bullet(\mathrm{B_{ae}} - \mathrm{c_{ae}}) + \mathrm{dq_r}\bullet(\mathrm{B_{ar}} - \mathrm{c_{ar}}) = 0 \tag{15a}$$

$$dq_a\bullet(\mathrm{B_{ba}} - \mathrm{cu_{ba}}) + \mathrm{dq_b}\bullet(\mathrm{B_{bb}} - \mathrm{cu_{bb}}) + \mathrm{dq_e}\bullet(\mathrm{B_{be}} - \mathrm{cu_{be}}) + \mathrm{dq_r}\bullet(\mathrm{B_{br}} - \mathrm{cu_{br}}) = 0 \tag{15b}$$

$$dq_a\bullet(\mathrm{B_{ea}} - \mathrm{cu_{ea}}) + \mathrm{dq_b}\bullet(\mathrm{B_{eb}} - \mathrm{cu_{eb}}) + \mathrm{dq_e}\bullet(\mathrm{B_{ee}} - \mathrm{cu_{ee}}) + \mathrm{dq_r}\bullet(\mathrm{B_{er}} - \mathrm{cu_{er}}) = 0 \tag{15c}$$

Dividing each expression by $dq_r$ and solving the equations, we can express the diversion ratios as:

$$D = \begin{bmatrix} \frac{dq_a}{dq_r} \\ \frac{dq_b}{dq_r} \\ \frac{dq_e}{dq_r} \end{bmatrix} = -(A^{\intercal})^{-1}\bullet\mathrm{B} \tag{16}$$

where the matrices $A$ and $B$ are the same as those defined above. With this result, we can see that the optimal second-best tariff for the ridesourcing mode should satisfy:

$$\tau_r = co_r + mec_r + E^{\intercal}\bullet\mathrm{D} \tag{17}$$

This leads to our final expression for the second-best tariff $\tau_r^{SB}$ for ridesourcing services:

$$\tau_r^{SB} = co_r + mec_r + D_{ar}\bullet\mathrm{mec_a} + \mathrm{D_{br}}\bullet(\mathrm{co_b} + \mathrm{mec_b} - \widetilde{\tau}_\mathrm{b}) + \mathrm{D_{er}}\bullet(\mathrm{co_e} + \mathrm{mec_e} - \widetilde{\tau}_\mathrm{e}) \tag{18}$$

where $D_{kr}$ is the diversion ratio between rides in mode $k$ and ridesourcing rides, and $mec_k$ is the marginal external cost for automobiles, buses and taxis defined in (6) and (7).

The first two terms on the RHS of Eq. (18) – operational costs and any externality caused by mode $r$ – are equivalent to the condition for the first-best fare given by (5d) for mode $r$, except that they are evaluated at a different vector of rides.

The diversion ratios measure the rate of ridesourcing rides that come from each of the other modes, and are negative under the (plausible) assumption that each mode is a substitute for the other. For example, if ridesourcing trips increase by 10, and 3 of these rides were previously undertaken by bus, then the diversion ratio between buses and ridesourcing trips is −0.3. If ridesourcing services are used to solve the 'last mile problem' in public transport services, then the diversion ratio between buses and ridesourcing could be positive (an increase in ridesourcing trips increases the number of bus trips). In general, the empirical literature shows that ridesourcing is both a substitute for and a complement to public transport, depending on the type of trip. Using data until 2015, Hall et al. (2018) estimate that Uber increases public transport ridership for the average public transport agency in the United States, but great heterogeneity in local effects is found. However, data from several cities (Clewlow and Mishra, 2017; Agarwal et al., 2019; Erhardt et al., 2021), including Santiago (Tirachini and del Río, 2019), show that the substitution effect is stronger than the complementary effect, particularly for urban buses.

The intuition behind condition (18) is that if are there externalities caused by automobiles, then the optimal fare for ridesourcing services should be lowered in a second-best scenario when these modes are substitutes. This will increase the use of ridesourcing services, reducing the number of rides in automobiles, which will help to reduce the negative externalities generated by this private mode, and thus improve welfare. This is what the third term on the right hand side of condition (18) represents. The fourth and fifth term of this condition have an analogous interpretation. If the fares for bus and taxi rides are below their operational cost and marginal external cost, then the optimal ridesourcing fare should be lowered to reduce rides in these two modes when they are substitutes to ridehailing services. On the other hand, if the bus fare is larger than operating cost and marginal external cost for this mode, i.e., $\tau_b > co_b + mec_b$, and ridesourcing and bus are substitutes ($D_{br} < 0$), then we have that $D_{br}\bullet\left(\mathrm{co_b} + mec_b - \tau_b\right) > 0$, which increases the second-best ridesourcing fare.

It is worth noting that this optimal second-best pricing model was derived using four modes; however, the formulation shown here is general enough to apply to an arbitrary number of modes. The extension of the optimal second-best fare (18) to $n$ modes is:

$$\tau_r^{SB} = co_r + mec_r + D_{ar}\bullet\mathrm{mec_a} + \sum_{\mathrm{k=2}}^{\mathrm{n-1}}\mathrm{D_{kr}}\bullet\left(\mathrm{co_k} + \mathrm{mec_k} - \tau_\mathrm{k}\right) \tag{18'}$$

where, without loss of generality, the first mode is assumed to be automobile trips and the last mode is assumed to be ridesourcing

[3] The diversion ratio between modes $k$ and $j$ can also be expressed as the ratio of the cross-elasticity of demand of mode $k$ with respect to the price of mode $j$ divided by the own price elasticity of mode $j$ multiplied by the ratio of rides: $\frac{dq_k}{dq_j} = \frac{\eta_{kj}}{\eta_{jj}}\bullet\frac{\mathrm{q_k}}{\mathrm{q_j}}$. We discuss the interpretation of these diversion ratios for the current application in more detail below.

trips (the mode being priced), under the assumption that there is no congestion charge for automobiles.

## 3. IPDL demand system

To empirically obtain the optimal fares for the first-best scenario, we need to find a vector of rides that simultaneously solve Eqs. (2) and (3), and in which the $\tau_k s$ in these equations are given by Eqs. (5a)–(5d). That is, the vector must be such that the willingness to pay for the last ride in each mode is equal to user cost plus the optimal first-best fare.[4] When all these conditions are met, optimal fares are given by (5a)–(5d), evaluated at the solution vector of rides. If applied, these fares would induce demand for rides equal to the solution vector, since consumers would undertake rides until the willingness to pay for the last ride would be equal to the cost they face (including time and financial costs). By subtracting the costs or fares currently faced by users from the optimal fares thus calculated, we obtain the optimal surcharge or subsidy over current fare levels for each mode.

To solve for the optimal ridesourcing fare in a second-best scenario, we follow a similar approach. In this case, we need to find a vector of rides that simultaneously meet conditions (2) and (3), but in which the fare for automobiles is zero, the fare for buses and taxis is equal to the current fare, and the fare for the ridesourcing mode is given by Eq. (18).

To empirically apply our model, then, we need a parametric representation of the left-hand sides of (2) and (3) as well as a parametric function relating rides with the congestion externality that affects the right-hand sides of these equations. In this section, we present the former, while in the next section, we show how rides affect congestion costs.

Note that the left-hand sides of (2) and (3) are a system of equations relating the willingness to pay for an additional ride in each mode to the number of rides in all modes. In turn, these functions are related to consumers' preferences for rides and their ensuing substitution patterns. In essence, we need an indirect demand system for rides in which willingness to pay for each mode is expressed as a function of rides for all mode.[5] This system should be flexible enough to accommodate arbitrary substitution patterns.

There are two alternatives here. One is to specify a flexible direct demand system and then invert it. This is the approach used by Berry et al. (1995), who specify a random coefficient logit model. Although this model allows for arbitrary substitution patterns between alternatives, it cannot be inverted analytically, and numerical techniques must be used to obtain the marginal willingness to pay for each good as a function of quantities. A less cumbersome approach would be to specify a direct demand system that can be inverted analytically, such as the nested logit model. However, this would require arbitrary assumptions regarding the nesting structure of the demands for the four modes in our problem.

The second alternative is to start by specifying a parametric inverse demand system. Previous research estimating optimal prices for multimodal transport systems, such as Ahn (2009), has taken this approach. However, to have a tractable model, Ahn (2009) specifies a linear inverse demand system with very restrictive substitution patterns. Until recently, available parametric inverse demand systems lacked sufficient flexibility to be a convenient approach to our four-mode application.

Recently, however, Fosgerau, Monardo and de Palma (2021) (hereafter FMP) propose a flexible, yet tractable, inverse demand system called the Inverse Product Differentiation Logit (IPDL) model. The IPDL model allows for flexible substitution patterns in a product differentiation context, while modelling the inverse demands directly. That is, the model makes it unnecessary to numerically invert a direct demand system such as that in Berry et al. (1995).[6]

To introduce the IPDL model, we begin by noting the result of Fosgerau and De Palma (2016) that any additive random utility model can be derived as the utility maximization of a representative consumer with the following quasi-linear utility function:

$$U(z,q) = \alpha \bullet \mathrm{z} + \beta^{'}\mathrm{q} + \Omega(\mathrm{q})$$

where $z$ is the quantity of a numeraire good, $q$ is a vector of quantities of the differentiated products, $\alpha$ is a parameter that corresponds to the marginal utility of income, $\beta$ is a vector of parameters conformable to $q$ and $\Omega(q)$ is a general entropy function to be discussed shortly. The representative consumer maximizes this utility subject to the budget constraint $y = z + p'q$ and a normalization

[4] Notice that the number of rides in each mode affects both the left-hand sides of Eqs. (2) and (3) and the right-hand side (through the impact of rides on the congestion externality and thus on each $\tau_k$). Note also that the solution involves solving a fixed-point problem.

[5] In economics, a demand function can have two interpretations. First, for a given price, the demand function will determine the quantity demanded. This is called a direct demand function, in which the quantity demanded is a function of prices or *q(p)*. Second, for a given quantity, the demand function gives the willingness to pay of a consumer for this last unit of consumption. This is called the inverse demand function, with *p*, willingness to pay, as function of quantities or *p(q)*. These two interpretations carry over to multiple demands. A demand system in which the quantity for each good is a function of the vector prices for all goods is called a direct demand system, while a demand system in which the willingness to pay for the last unit consumed of each good is a function of the vector of consumption of all goods is called an inverse demand system. They are both valid representations of consumer preferences. In the case of one good, inverting the direct demand to obtain the indirect demand is trivial. However, in the multi-good case, inverting the direct demand system to obtain the indirect demand system is challenging, and often there is no analytical expression for the inverted system.

[6] Unlike the nested logit, the IPDL model also allows for certain goods to be complements rather than substitutes. However, in our application, ridesourcing and buses are substitutes given the empirical evidence available for Santiago and the product differentiation structure we adopt in the model, as discussed further below.

constraint for the differentiated good $\sum_{j\in J} q_j = 1$.

The general entropy function is defined as $\Omega(q) = -q'\ln G(q)$, where $G(q)$ is a continuous, homogenous of degree one, concave, differentiable and globally invertible vector function. This entropy function represents the taste for variety of the representative consumer.[7]

For example, Anderson et al. (1988) show that if the entropy function is defined as the Shannon entropy measure ($\Omega(q) = -q^{'}\ln q = -\sum_i q_i \bullet \ln q_i$), the resulting demands are identical to the logit model. Fosgerau and de Palma (2016) show that if the set of $J$ differentiated products is partitioned into $\mathscr{G}$ mutually exclusive hierarchical groups and the $j^{th}$ component of $G(q)$ is defined as $G^{(j)}(q) = q_j^{\mu_{g_j}} \bullet \left(\sum_{i\in \mathscr{G}_j} q_i\right)^{(1-\mu_{g_j})}$, where $\mu_{\mathscr{G}_j}$ is a parameter between 0 and 1 and $\mathscr{G}_j$ is the group to which good $j$ belongs, then the resulting model is the nested logit model.

The IPDL model is a generalization of the above two examples. By suitably defining $G(q)$ in the general entropy function, it is possible to obtain an indirect demand system that is tractable, yet more flexible than the logit or nested logit model. The IPDL model contains the logit and nested logit as special cases.

To define the IPDL model, we present the notation for our application. Following FMP, utility for the representative consumer is assumed to be quasi-linear:

$$U(z, s_0, s_a, s_b, s_e, s_r) = \alpha \bullet z + \sum_{k=\{0,a,b,e,r\}} \beta_k \bullet s_k - \sum_{k=\{0,a,b,e,r\}} s_k \bullet \ln G_k(s_0, s_a, s_b, s_e, s_r) \tag{19}$$

where $\alpha$ is the marginal utility of income, $z$ is the numeraire good, $s_k$ are the share of rides in mode $k$, including an 'outside' mode 0, and the function $lnG_k$ of the general entropy measure is defined as:

$$lnG_k = \left(1 - \sum_{d=1}^{D} \mu_d\right) \bullet \ln(s_k) + \sum_{d=1}^{D} \mu_d \bullet \ln\left(\sum_{j\in \mathscr{G}_d(k)} s_j\right) \tag{20}$$

where $D$ is the number of dimensions along which the differentiated goods can be segmented, forming specific (not mutually exclusive) nests to be discussed further below, $\mathscr{G}_d(k)$ is the set of products belonging to same nest as $k$ in the product segmentation dimension $d$, and $\mu_d$ are non-negative parameters associated with each dimension of product differentiation (with $\left(1 - \sum_{d=1}^{D} \mu_d\right) > 0$).

In the utility function (19), the first two terms measure the utility derived from consuming the numeraire good and the set of differentiated goods, which in our application are different transport mode shares. As already discussed above, the last term represents the value from the variety of the differentiated good (transport modes).

To obtain the demand functions for each mode, the consumer maximizes utility subject to the budget constraint $\sum_k p_k \bullet s_k + z = y$ (where $y$ is income). Substituting the budget constraint into Eq. (19) and considering the summing up restriction $\sum_k s_k = 1$, leads to the following Lagrange function:

$$\mathscr{L} = \alpha \bullet y + \sum_k (\beta_k - \alpha \bullet p_k) \bullet s_k - \sum_k s_k \bullet \ln G_k(s_0, s_a, s_b, s_e, s_r) + \lambda \bullet \left(1 - \sum_k s_k\right)$$

Maximizing this function with respect to each modal share, we obtain the first-order conditions that determine the consumer's optimal demands:[8]

$$lnG_k(s_0, s_a, s_b, s_e, s_r) = \beta_k - \alpha \bullet p_k - (1 + \lambda) = \beta_k - \alpha \bullet p_k - c \tag{21}$$

where $c$ is a constant equal to one plus the Lagrange multiplier of the summing up restriction ($\lambda$).

As for the dimensions $D$ of market segmentation, these are different characteristics of the goods that define a finite number of groups along each dimension. Each good belongs to only one group (or nest) along each dimension. When the different market segmentations have a hierarchical order, FMP show that the IPDL model collapses to the well-known nested multinomial logit. However, the function $lnG_k$ is more flexible, in the sense that it allows for a non-hierarchical nesting structure.

This last feature is attractive in the current application. Ridesourcing services share characteristics that assimilate them to taxi and private automobile travel; namely, door to door services. At the same time, it shares the feature of buses (and taxis) of being a mode in which users do not own the vehicles, providing motorized mobility to non-car owners. Moreover, in the case of buses, ridesourcing and taxis, passengers are not completely alone in the vehicles, and using them involves procuring a ride and waiting for it. These different dimensions are not hierarchical, and the IPDL model is therefore useful in the current application.[9]

[7] The idea of using a representative consumer with a taste for variety to model differentiated product markets goes back to Dixit and Stiglitz (1977). That this last term represents taste for variety can be understood by noting that if this term disappears, then the representative consumer will consume only one variety of the differentiated good (the one that gives them the highest net utility), while if it is large, the consumer will consume an equal amount of each variety (see Anderson et al., 1988).

[8] Notice that when taking the derivative of the Lagrange function with respect to each $s_j$ there will be a term equal to $\sum_k s_k \bullet \frac{\partial \ln G_k}{\partial s_j}$. It is easy to verify that this term equals 1. See Proposition 5.3 in Fosgerau et al. (2021).

[9] If passengers first chose an individual versus a shared mode, and then those that chose the shared alternative decided among individual public transport modes (taxis or ridesourcing applications) and mass transit mode (buses), then the nesting would be hierarchical, and the nested multinomial logit could be applied.

We chose two dimensions for the segmentation of the different modes. First, an individual door-to-door motorized travel mode (with associated parameter $\mu_I$) and a shared motorized transport mode (with associated parameter $\mu_{TP}$). The nesting structure of these two dimensions is shown in Table 1.

In the door-to-door transport dimension, we have taxis, ridesourcing services and private automobiles, while buses are not door-to-door transportation modes. In the shared transport dimension, we have taxis, ridesourcing services and buses; automobiles are not shared transport modes. Only taxis and ridesourcing services are both door-to-door services and shared transport modes. This last overlap is what differentiates the IPDL model from the hierarchical structure of a nested multinomial logit model.[10]

Given the assumptions of Table 1, the different sets segmenting the goods to calculate Eq. (20) would be $\mathscr{G}_I : \{a, e, r\}$ and $\mathscr{G}_{TP} : \{b, e, r\}$. The outside (other and non-motorized) transport mode is in a segment by itself. Therefore, Eq. (20) for this mode collapses to:

$$lnG_O = ln(s_O) = \beta_O - c = -c \tag{22}$$

where the last equality follows from normalizing the net utility from to outside transport mode to zero.

One final point regarding the IPDL model that will be used for parametrization. Using (20), (21) and (22), it is easy to show that:

$$ln\left(\frac{s_k}{s_O}\right) = \beta_k - \alpha \bullet \mathrm{p_k} + \sum_{\mathrm{d}=1}^{\mathrm{D}} \mu_\mathrm{d} \bullet \ln\left(\frac{\mathrm{s_k}}{\sum_{\mathrm{j} \in \mathscr{G}_\mathrm{d}(\mathrm{k})} \mathrm{s_j}}\right) \quad \text{for} \quad \mathrm{k} \neq \mathrm{O} \tag{23}$$

Eq. (23), along with other restrictions that will be presented below, allows us to calibrate the demand parameters.[11]

Eq. (23) gives an inverse demand system for the consumption of each mode in the sense that we can solve for price of each differentiated product as a function of parameters and the vector of shares. This will represent the marginal willingness to pay for an additional ride as a function of the demand for all the differentiated products. By solving for each price, we thus obtain an expression equivalent to Eq. (1) in Section 2 of the paper, which, together with Eqs. (2) and (3), allows us to parametrize the model and then use it for the simulations.

To make the simulation approach clearer, once we have a suitably parametrized version of Eq. (23) for each mode, we can solve for the vector of shares ($s_k$) such that each $p_k$ from Eq. (23) is equal to the social cost of an additional ride for each mode given by Eqs. (5a)–(5d) in the first-best scenario. In the second-best scenario, we find the vector of mode shares that makes the willingness to pay for an additional ridesourcing ride ($p_r$ from Eq. (23) for this mode) equal to the user time cost plus the optimal second-best fare given by Eq. (18).

## 4. Application

In this section, we apply our model to the city of Santiago, Chile. Two comments are in order. First, in the derivation of the first-best and second-best optimal tariffs, we have ignored any capacity constraint on the bus and taxi modes. This is reasonable in the context of Santiago given that the bus fleet was not reduced after the entry of ridesourcing applications such as Uber and Cabify more than 5 years ago. The same applies for taxis. Although the price of a taxi medallion has likely fallen in Chile since the entry of ridesourcing applications, it is still positive, implying that taxi owners still obtain a scarcity rent from their vehicles. Therefore, there are incentives to operate the full fleet of taxis in Santiago.[12] In any case, if we included a capacity constraint in the above optimization problem, the result would be that the average cost of these modes would include a marginal capacity cost in addition to operating costs (Tirachini and Hensher, 2012). Second, in what follows, we assume there are constant economies of scale in operating costs. This is reasonable for all modes, including buses.

### 4.1. Time costs

Time cost for the automobiles, taxis and ridesourcing services is given by a BPR (*Bureau of Public Roads*) function, which has been calibrated for urban roads in Santiago (SECTRA, 2005):

$$cu_a = VoT \bullet \mathrm{t_0} \bullet \left(1 + \alpha_{\mathrm{BPR}} \bullet \left(\frac{\mathrm{f_a} + \mathrm{f_e} + \mathrm{f_r} + \mathrm{F} \bullet \mathrm{f_b}}{\mathrm{CAP}}\right)^{\beta_{\mathrm{BPR}}}\right) \tag{24}$$

[10] Given the nesting structure of Table 1, ridesourcing and buses can only be substitutes given that in some dimensions, they belong to the same nest (Fosgerau et al., 2021). The only possibility for these two services to be complements would be if they never belonged to the same nest in any dimension. However, testing such a nesting structure gives inconsistent results compared to those in Table 1. Also, the empirical evidence regarding diversion ratios and other evidence presented in the next section indicate that these services are substitutes in the case of Santiago.

[11] To highlight the relationship between this model and discrete choice models with analytical expressions for the inverse demand, the right-hand side of (23) does not include the last term in the case of the multinomial logit model. In the case of the nested logit, the last term involves the group and sub-groups to which $k$ belongs in the hierarchical structure of the problem. The IPDL model is more general, allowing for more flexible substitution patterns.

[12] The fact that neither the bus fleet nor the taxi fleet have declined allows us to ignore waiting time considerations in the demand for these modes. We assume frequencies, and thus waiting times, have remained fairly constant throughout this period. There is an effect of changes in congestion on waiting times that we do not model. On this last point, see the discussion in the conclusion.

**Table 1**
Nesting structure for the current application.

| | | Shared motorized vehicles | |
|---|---|---|---|
| | | **Yes** | **No** |
| **Door-to-door service** | **Yes** | Taxi, Ridesourcing | Automobile |
| | **No** | Bus | Other |

The simplicity and parsimony of BPR function explain its popular use in congestion and traffic assignment studies. In (24), *VoT* is the monetary value of time, $t_0$ is free-flow travel time, $f_k$ is the number of vehicles in the road for each mode, given by $f_k = \frac{q_k}{K_k}$, where $K_k$ is the number of passengers per vehicle in each mode, $F$ is a parameter that measures the equivalence in saturation flow between a standard automobile and a bus, *CAP* is network road capacity, and $\alpha_{BPR}$ and $\beta_{BPR}$ are parameters of the BPR function. In the case of buses, the free-flow time is penalized by a parameter $M$ given that a bus will be slower than the other modes owing to stops to pick up or alight passengers:

$$cu_b = VoT \bullet (\mathrm{t_0} \bullet \mathrm{M}) \bullet \left(1 + \alpha_{\mathrm{BPR}} \bullet \left(\frac{\mathrm{f_a} + \mathrm{f_e} + \mathrm{f_r} + \mathrm{F} \bullet \mathrm{f_b}}{\mathrm{CAP}}\right)^{\beta_{\mathrm{BPR}}}\right) \tag{25}$$

The $\alpha_{BPR}$ and $\beta_{BPR}$ values have been calibrated for several road types using empirical data on vehicle flows and travel times (see, e.g., Mtoi and Moses, 2014). For the case of Santiago, these congestion parameters were calibrated by SECTRA (2005). Depending on the road type, for urban roads $\alpha_{BPR}$ is between 1.0 and 1.6, and $\beta_{BPR}$ is between 2.8 and 7.7 (SECTRA, 2005), where the largest values of $\beta_{BPR}$ come from roads with large bus flows. In other contexts where there is a lack of local data, a standard value $\beta_{BPR} = 4$ is often chosen (Mtoi and Moses, 2014; Tirachini et al., 2014). In Santiago, prior to the public transport reform implemented in 2007 (called Transantiago), bus operation was extremely inefficient at stops, with long stop times due to users' cash payments to drivers, and drivers' incentives to wait at stops until vehicles were sufficiently filled. These issues help explain the large value of $\beta_{BPR}$ on roads with buses prior to 2007. The introduction of cashless fare transactions by means of a smartcard has significantly reduced bus stop times in Santiago (Fernández et al., 2008). We therefore use $\alpha_{BPR} = 1.3$ and $\beta_{BPR} = 4$ as base values for our congestion functions.

Data collected for Uber trips in Santiago (Fielbaum and Tirachini, 2021) indicate a free-flow speed of 30 km/h (including stops at intersections, but not interactions with other vehicles) and an average speed of 24 km/h during the day, values that are used to calibrate CAP in Eq. (24), which is obtained as $CAP = 6{,}274$ passenger car units. This approach is equivalent to assuming a given road with a fixed capacity (for instance, a 2-lane road with 4,000 passenger car units per hour as capacity) and instead of calibrating the capacity, calibrating the modal flows that reproduce observed modal shares as in Table 2 (further below) and observed speeds.

In what follows, currency is converted from Chilean pesos (CLP) to US dollars (USD), using the average exchange rate during 2019 of USD 1 = CLP 703, according to the Chilean Central Bank. The official value of time (*VoT*) estimate of USD $3.13 per hour and an average daily capacity utilization factor of $K_b = 27$ for buses, $K_a = 1.46$ for automobiles and $K_e = 0.58$ for taxis are used, based on SECTRA (2013). In the case of taxis, this parameter accounts for the fact that taxis travel without passengers some of the time. We assume ridesourcing applications are more efficient in this respect and have a $K_r = 0.8$.[13]

The equivalency factor of buses depends on vehicle size. In Chile, the official recommendation is to use 1.65 for 8-metre-long buses, 2.0 for 12-metre-long buses and 3.0 for 18-metre-long buses (MDS-SECTRA, 2013). In Santiago, 18.6% of the fleet is composed of 8-metre-long buses, 68.3% of 12-metre-long buses and 13.1% of 18-metre-long buses (DTPM, 2019). Then, the weighted average bus-car equivalency factor is $F = 2.1$. The extra time for a trip on a bus is assumed to be $M = 1.25$, based on actual bus stop delays estimated in Santiago (Cubillos, 2018).

### 4.2. Mode shares

We define the mode shares before the entry of ridesourcing applications. Since we do not have information on the mode shares after entry of these applications, these will be estimated as explained below.

Table 2 presents the information from the 2012 Origin-Destination survey for Santiago (SECTRA, 2014), with data collected prior to the entry of ridesourcing applications. The table indicates that 25.7% of trips in a working day were undertaken by automobile, 25.0% by public transport (bus and/or metro), and 1.7% by taxi.[14] In what follows, we assume these same shares in our application.

For calibration, the shares shown in the last column of Table 2 are denoted as $s_{k/r}$, denoting the shares for mode $k$ prior to the availability of the ridesourcing option.

### 4.3. Operational costs and fares

Trip length is assumed to be 8.0 km, which is the average trip distance for taxi, auto and bus trips in Santiago (SECTRA, 2014).

[13] This assumes that ridesourcing is 30% more efficient in reducing empty kilometres than street-hailing (Tirachini and Gomez-Lobo, 2020).

[14] Cycling and walking account for most of the rest of the trips, with a combined modal share of 38.5%. We include 22% of metro-only public transport trips in the analysis. Excluding these trips does not affect the results.

**Table 2**
Modal shares, Santiago 2012 (normal working day).

| Mode | Number of trips (thousand) | Share |
|---|---|---|
| Private automobile | 4,748.6 | 25.7% |
| Bus/public transport | 4,621.4 | 25.0% |
| Taxi | 315.0 | 1.7% |
| Ridesourcing services | — | — |
| Other | 8,776.1 | 47.5% |
| Total | 18,461.1 | 100.0% |

*Source*: SECTRA (2014). The Other category is mostly walking and to a lesser extent cycling.

Average speed in the city is 24 km/h, which is estimated as the average speed of Uber trips in Santiago with data collected in Fielbaum and Tirachini (2021). A taxi trip has a fixed fee of USD 0.427 plus a variable charge of USD 0.185 per 200 meters or 60 seconds (whichever happens first). Therefore, the total fare for a taxi ride of 8.0 km would be USD 7.82. When dividing this by 1.3, the average number of passengers per taxi trip, we obtain USD 6.02 per person ($\tau_e$).

For ridesourcing applications, we use Uber fares for Santiago, which consisted of a USD $ 0.64 fixed charge plus USD $ 0.313 per kilometre variable charge and USD $ 0.114 per minute. Assuming the 24 km/h speed as well, the average trip would cost USD 5.42. When this figure is divided by 1.5, the average number of passengers per trip, we obtain a fare per passenger equal to USD 3.61 ($\tau_r$). For bus trips, the fare was USD 0.97 ($\tau_b$).

Operational costs for each mode are the following. For taxis and ridesourcing services, we use the results of Bennett and Zahler (2018), who estimate the operational costs, including driver wages and kilometres without passengers, for these modes. Per kilometre, the average operational cost for taxis is USD $ 0.797/km, and for ridesourcing services it is USD $ 0.579/km. Scaling these figures for an 8-kilometre ride and considering the number of passengers per trip for each mode to adjust this cost to a per-passenger basis, we obtain USD $ 4.90 per trip per passenger in a taxi ($co_e$) and USD $ 3.09 per trip per passenger in a ridesourcing vehicle ($co_r$). [15]

For a car trip, the user costs are a bit more complex. We assume that the average life of a car is 300,000 km.[16] We also assume an initial cost of the automobile of CLP $ 10 million (around USD $ 14,200). Therefore, assuming linearity for simplicity, we compute a depreciation cost of USD $ 0.05 per kilometre. The price of gasoline (95 octane) was USD $ 1.16, and assuming 11 km per litre as the average fuel consumption, we arrive at a fuel cost of USD $ 0.11 per kilometre. To this, we add insurance costs (CLP $40,000 per month), parking (CLP $ 20,000 to CLP $ 80,000 per month, assuming CLP $ 50,000 as the central value) and CLP $ 200,000 yearly maintenance. An assumed average of 2,000 km travelled per month these add CLP $ 53.3 (USD $ 0.08) to user costs. In sum, the cost of an 8-kilometre trip by automobile is USD $ 1.83 ($co_a$), or USD $ 1.25 per passenger assuming an average of 1.46 passengers per car trip.

Finally, for buses, we estimate a total cost of USD $ 1.60 per kilometre, based on Librium (2013). This value includes all running costs, driver costs, maintenance, depreciation and administration costs, and have been updated to December 2018 using the accumulated inflation rate between July 2013 and December 2018 (19.9%). Multiplying this figure by the average trip length (8 km) and dividing by the average daily bus capacity utilization (27), we arrive at an average operating cost of USD $ 0.48 ($co_b$).

### 4.4. *Diversion ratios and post entry market shares*

As reported in Tirachini and Gomez-Lobo (2020), survey information is available for Santiago as to which mode ridesourcing users would use if the application were not available for their latest (surveyed) ridesourcing trip. The results are presented in Table 3.

As discussed in Conlon and Mortimer (2020), these 'second choice' questions are common in consumer surveys, and correspond to diversion ratios that measure the average treatment effect of product removal. Furthermore, defining $s_{k/r}$ as the market share of mode $k$ when ridesourcing applications are not available and $s_k$ when they are available, Conlon and Mortimer (2020) argue that these diversion ratios are equal to:

$$D_{kr} = \frac{s_{k/r} - s_k}{s_r}, \quad k \in \{a, b, e, o\} \tag{26}$$

where $D_{kr}$ is the diversion ratio from $r$ to $k$ from removing the ridesourcing applications.

Therefore, the diversion ratios reported in Table 3 can be used to obtain the post-entry market shares of each mode, including the ridesourcing application. However, an additional assumption is needed, and we assume that the share of ridesourcing post entry is equal to the share of taxi rides.[17] We later discuss the sensitivity of results to this last assumption and other parameters.

The results are presented in Table 4. The ridesourcing services reduce the use of all other modes, including the outside mode, but the largest reduction in relative terms is for taxis. The market share of this last mode decreases from 1.7% to 1.2%, or 88.4 thousand trips per day. In absolute terms, this is close to the reduction in the number of bus trips (81 thousand per day), but the relative fall for

[15] Note that these cost estimates imply a positive margin of fares over costs for taxis and ridesourcing. In the case of taxis, this is reasonable, since there are rents in this industry that are reflected in a positive value of taxi permits (medallions). The margin for ridesourcing is smaller, and may be due to market power of these applications.

[16] This is an approximate figure; usual values are in the range 240,000–320,000 km. See, e.g., Lu (2006).

[17] There are five post-entry modal shares and only four equations (26). The summing-up restriction is already implicit in these equations.

**Table 3**
Alternative mode of transport under the hypothetical scenario that ridesourcing services are not available, Santiago.

| Mode | share of trips |
|---|---|
| Automobile | 0.12 |
| Bus | 0.36 |
| Taxi | 0.39 |
| Others | 0.13 |

*Source:* Tirachini and Gomez-Lobo (2020)

this mode is smaller owing to the larger initial number of trips.

### 4.5. Demand calibration

Given all the above time cost parameters, operational cost parameters, fares and modal shares, both before and after the entry of the ridesourcing applications, it is possible to calibrate the demand model to replicate these outcomes. This is done through the following procedure.

We reproduce Eq. (23) of the demand model once again, but slightly transformed:

$$ln\left(\frac{s_k}{s_O}\right) - \beta_k + \alpha \bullet \mathrm{p_k} - \sum_{\mathrm{d=I,TP}} \mu_{\mathrm{d}} \bullet \ln\left(\frac{\mathrm{S_k}}{\sum_{\mathrm{j} \in \mathscr{G}_{\mathrm{d}}(\mathrm{k})} \mathrm{S_j}}\right) = 0 \tag{27}$$

Note that with the shares and price information (generalized price including the time cost component), we have seven equations from condition (27), in seven unknowns, namely $\beta_a, \beta_b, \beta_e, \beta_r, \alpha, \mu_I$ and $\mu_{TP}$. Three of these conditions relate to the modal shares and generalized price for the scenario prior to the entry of ridesourcing platforms, one for each of the three original modes. The four other conditions refer to the same restrictions for the scenario after entry, which now includes an additional equation for the ridesourcing mode. Prices differ between these two scenarios given that the average time cost will change with the change in the number of rides in each mode. Also, the summation of the denominator of the last terms of Eq. (23) must be adjusted to reflect whether ridesourcing services are or are not available. We also include a parameter, $\beta_{s/r}$, to scale $\beta_a, \beta_b, \beta_e$ for the scenario prior to the entry of the ridesourcing platform. That is, for these three modes, the modal constant before entry of the ridesourcing platform is $\beta_{s/r} \bullet \beta_{\mathrm{k}}$. We include this parameter because we expect that the modal constants change between a scenario with three modes compared to a scenario with four modes. We cannot calibrate this last parameter, since the system would then be underdetermined. We have exogenously assigned a value of 5 for $\beta_{s/r}$.[18]

We find $\beta_a, \beta_b, \beta_e, \beta_r, \alpha, \mu_I$ and $\mu_{TP}$ by equating each condition (27) to zero. The results are shown in Table 5.

The first thing to note is that the $\mu$ parameters are both positive and their sum is less than one. The marginal utility of income, $\alpha$, is also positive.

Table 6 presents the estimated own and cross-price elasticities for each mode. The own price elasticities are negative in each case. For automobile travel and bus travel, demand is inelastic as expected, while demand for taxis and ridesourcing platforms is elastic. These last two elasticities are larger than what might be expected given the available estimates from the literature.[19] This may be due to a higher price sensitivity for these modes in a developing country context. If the elasticities for these two modes have been overestimated (in absolute value), it would imply that the simulation results shown below underestimate the optimal first-best fares for these services, but overestimate the second-best fares for the ridesourcing mode.[20]

The results also indicate that all cross-price elasticities are positive, implying that all modes are substitutes for one another. As expected, an increase in the price of taxis will have a proportionally higher positive impact on ridesourcing demand compared to other modes and vice versa.

## 5. Results

With the calibrated inverse demand model, it is then possible to calculate the first-best fares for each mode and the second-best fare for ridesourcing services using the conditions developed in Sections 2.1 and 2.2.

The first-best results are shown in Table 7, where for comparability, we also show the current value for the fare and number of rides for each service.

[18] We tested values between 1.5 and 10 for this parameter, and the simulation results were nearly identical.

[19] Rose and Hensher (2014) report taxi demand elasticities that range from −0.35 to −1.4, taken from 13 different studies. For ridesourcing, Cohen et al. (2016) report elasticities between −0.4 and −0.6. See also Gibson and Carnovale (2015) for a list of automobile demand elasticities.

[20] The absolute values of the diversion ratios in equation (18) are inversely related to the absolute value of the own price elasticity of the ridesourcing service (see footnote 3). Therefore, the second-best adjustment is larger if demand for ride-sourcing services is less elastic, reducing the optimal second-best fare.

**Table 4**
Pre-entry and post trips and shares by mode.

| Mode | Pre-entry (2012) | | Estimated post-entry | |
|---|---|---|---|---|
| | Trips (thousands) | Shares $s_{k/r}$ | Trips (thousands) | Shares $s_k$ |
| Automobile | 4,748.6 | 25.7% | 4,721.4 | 25.6% |
| Bus | 4,621.4 | 25.0% | 4,539.8 | 24.6% |
| Taxi | 315.0 | 1.7% | 226.6 | 1.2% |
| Ridesourcing | — | — | 226.6 | 1.2% |
| Other | 8,776.1 | 47.5% | 8,746.6 | 47.4% |
| Total | 18,461.1 | 100.0% | 18,461.1 | 100.0% |

*Source*: The first two columns are from Sectra (2014); they are the same as in Table 2. The last two columns are estimated using diversion ratios from Tirachini and Gómez-Lobo (2020).

**Table 5**
Calibrated demand system parameters.

| Parameter | Value |
|---|---|
| $\beta_a$ | −0.0013 |
| $\beta_b$ | −0.0020 |
| $\beta_e$ | 0.0298 |
| $\beta_r$ | −0.6025 |
| $\alpha$ | 0.0004 |
| $\mu_I$ | 0.0677 |
| $\mu_{TP}$ | 0.5204 |

*Source*: own calculations.

**Table 6**
Own and cross-price elasticities of demand.

| | Price | | | |
|---|---|---|---|---|
| **Mode** | Automobile | Bus | Taxi | Ridesourcing |
| Automobile | − 0.46 | 0.06 | 0.04 | 0.02 |
| Bus | 0.08 | − 0.24 | 0.11 | 0.07 |
| Taxi | 0.16 | 0.37 | −3.70 | 0.08 |
| Ridesourcing | 0.16 | 0.37 | 0.14 | −2.22 |

*Source:* own calculations.

The results indicate that in a first-best scenario, there would be a congestion charge of USD $ 0.87 per person per trip for the automobile mode (USD 1.27 per automobile trip considering an average occupancy rate of 1.46 persons). The bus mode would receive a fare reduction of USD $ 0.39 per ride (a fare decrease of 40.7%) owing to its lower operating costs and the lower congestion externality. The taxi mode and the ridesourcing mode should be taxed in the optimal scenario, by 29.4% per ride in the case of ridesourcing services (USD 1.06 per passenger per trip or USD 1.59 per trip considering an average occupancy rate of 1.5).

As for the number of rides, they would fall by 16.6% in automobiles, decrease by close to 50% in the taxi and ridesourcing modes, and increase substantially (20.3%) for the most efficient mode, buses.

The intuition for these results is the following. All modes are charged their marginal social cost, including the congestion externality generated. For cars, taxis and ridesourcing, this is positive, while for buses, the social cost is lower than the current fare. The results are what is to be expected: an increase in the price of the less efficient modes, and a reduction in the price of the efficient mode.

Table 8 presents the results for a second-best scenario in which the only instrument available to the authorities is a charge for ridesourcing services. Fig. 1 compares these results to the base scenario and first-best outcome.

The results indicate that the second-best ridesourcing surcharge is USD 2.13 per passenger ride, 58.8% higher than in the base scenario. This reduces demand for ridesourcing services more than in the first-best scenario. Automobile, bus and taxi rides increase as the substitute mode is made more expensive. Although this increases the externalities generated by taxis and private automobiles, they are more than compensated for by the reduction in externalities as users move from ridesourcing services to public transport.

It is interesting to note that the welfare gains in the second-best scenario are only about one fifth (17.8%) of the welfare gains from the first-best scenario. This is because ridesourcing accounts for a small fraction of demand compared to those of cars and buses. Therefore, although welfare improves when only the ridesourcing mode is charged a tax, there is much to be gained by a policy that can also change the prices of the other modes. A second-best scenario could reach larger welfare gains in cities where ridesourcing already account for a large proportion of demand. An example is the city of San Francisco (the cradle of ridesourcing companies Uber and Lyft), where in 2016, ridesourcing accounted for at least 9% of the city modal share (SFCTA, 2017).

**Table 7**
First-best fares and rides.

| | Automobile | Bus | Taxi | Ridesourcing |
|---|---|---|---|---|
| **Fares: (USD per trip per passenger)** | | | | |
| Current value | 0 | 0.97 | 6.02 | 3.61 |
| First-best value | 0.87 | 0.57 | 7.09 | 4.68 |
| Optimal surcharge | 0.87 | −0.39 | 1.07 | 1.06 |
| surcharge/current values (%) | — | −40.7% | 17.8% | 29.4% |
| **Rides: (thousand)** | | | | |
| Current value | 4,721 | 4,540 | 227 | 227 |
| First-best value | 3,937 | 5,463 | 112 | 113 |
| Difference | −784 | 923 | −115 | −114 |
| Difference/current value (%) | −16.6% | 20.3% | −50.6% | −50.3% |

**Table 8**
Second-best fares and rides.

| | Automobile | Bus | Taxi | Ridesourcing |
|---|---|---|---|---|
| **Fares: (USD per trip per passenger)** | | | | |
| Current value | 0 | 0.97 | 6.02 | 3.61 |
| Second-best value | 0 | 0.97 | 6.02 | 5.74 |
| Difference | 0 | 0 | 0 | 2.13 |
| surcharge/current values (%) | — | — | — | 58.8% |
| **Rides: (thousand)** | | | | |
| Current values | 4,721 | 4,540 | 227 | 227 |
| Second-best values | 4,764 | 4,659 | 233 | 68 |
| Difference | 43 | 119 | 7 | −158 |
| Difference/current value (%) | 0.9% | 2.6% | 2.9% | −69.9% |

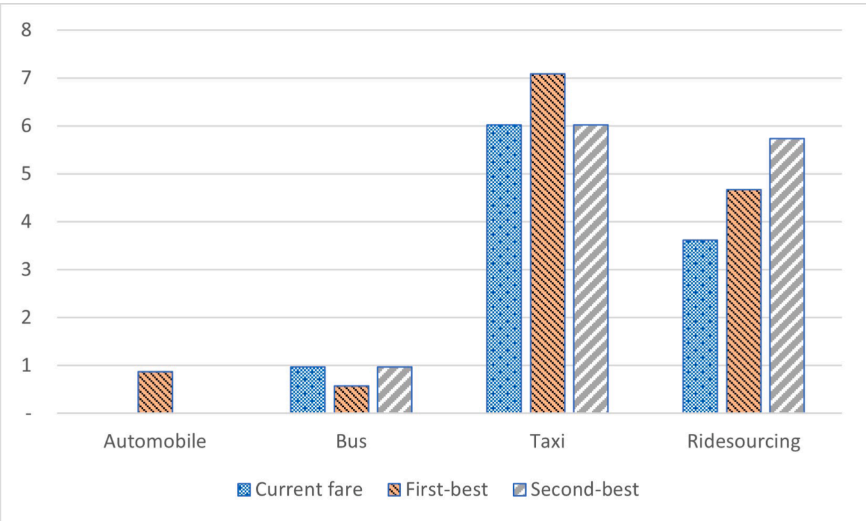


**Fig. 1.** Optimal fares compared to benchmark scenario (USD/passenger).

## 6. Sensitivity analysis

In this section, we perform a sensitivity analysis of three relevant assumptions or parameters. These are the following:

- the assumption made in Section 4.4 that ride-hailing share was equal to the taxi share after entry by the ridesourcing mode;
- the $\beta_{BPR}$ parameter of the BPR function, which determines the convexity of the flow-delay travel time function;

- and the average number of passengers per ridesourcing trip, since it has been shown that increasing the occupancy rate of ridesourcing vehicles reduces the effect of these services in terms of vehicle-kilometres travelled (Tirachini and Gomez-Lobo, 2020).

With respect to the initial relative share of the ridesourcing mode to the taxi mode used to obtain the results in the last two columns of Table 4, a recent online sample (n = 3222) shows a larger demand for ridesourcing than for taxis in Santiago in early March 2020, before the beginning of the COVID-19 crisis (Astroza et al., 2020). In this sample, the demand for ridesourcing was found to be 3.4 times that for taxis. Given the online data collection method used, there might be a bias in favour of ridesourcing in this study. Therefore, in a sensitivity analysis, we assume that the initial ridesourcing demand was 2 to 3 times the demand for taxis.

Table 9 presents the results, where for comparison, we reproduce the results of the baseline scenario. It can be seen that the baseline results are not overly sensitive to this parameter. There is a slight increase in the first-best surcharge and a slight decrease in the second-best surcharge, but the changes are minor.[21]

Table 10 presents the results of varying the $\beta_{BPR}$ parameter.[22] If $\beta_{BPR}$ is set to 3 instead of 4, the optimal charge falls from 29.4% of the original fare in the baseline scenario to 26.1%. If $\beta_{BPR}$ is set to 5, it increases to 30.7%, as the congestion externality becomes more pronounced. Thus, the optimal first-best fare is not very sensitive to this parameter.

In contrast, the second-best fare is much more sensitive to the BRP function parameter. The optimal charge falls from 58,8% of the original fare in the baseline scenario to 41.5% if a lower $\beta_{BPR}$ value is used, and increases to 75,3% if a higher value is used. Thus, in a second-best environment, it may be important to calibrate this function precisely.

The final sensitivity analysis undertaken is with respect to the average number of passengers per ridesourcing trip.[23] Our baseline scenario assumes 1.5 passengers on average. We increase this number to 2 and 2.5. The results are shown in Table 11.

Both in the first-best scenario and the second-best scenario, the optimal surcharge for the ridesourcing mode increases slightly in proportional terms. The intuitive reason for this result is that, while a higher occupancy rate reduces the negative externality per passenger caused by the ridesourcing mode, it also reduces the fare per passenger, increasing demand and syphoning more passengers from the relatively more efficient public transport mode.[24] This second effect dominates in the externality calculation, and the tax rate should be increased somewhat to counter the incentives to use the ridesourcing mode. However, the per-passenger fare including this charge is still lower than in the baseline scenario, and the use of this mode is substantially higher.

The results from varying the occupancy rate have other implications as well. An increase in ridesourcing fares through an optimal fist-best or second-best surcharge would probably change the occupancy rate. That is, as ridesourcing fares become more expensive, users may have incentives to share rides.[25] Related to this issue is the empirical finding that sharing a ridesourcing ride is more likely for low-income users than for high-income users in Santiago (Tirachini and del Río, 2019). Our simulations assume that the occupancy rate is constant as fares change. However, as shown above, endogenizing the occupancy rate according to the fare charged will probably not change the optimal proportional surcharge by much, since this surcharge is not overly sensitive to the occupancy rate.

## 7. Conclusions

As more competition enters the transport market and prices for ridesourcing services fall, optimal second-best fares may imply a surcharge on ridesourcing rides. We use a novel flexible inverse demand system to study this issue in a four-mode setting, including automobiles, buses, taxis and ridesourcing services. We parametrize the model for the case of Santiago, Chile.

For our case study, in a first-best scenario in which automobiles and taxis can be charged a congestion tax and buses can be subsidized, the results show that there is still an optimal 29.4% surcharge on ridesourcing services to internalize the congestion externality generated by this mode. In a second-best scenario, in which the only available policy instrument is a charge on ridesourcing services, the optimal charge for this mode increases to 58.8% of the fare. However, the welfare gains from second-best pricing are only 17.8% of the welfare gains from first-best pricing. Therefore, from a policy perspective, there is much to be gained from having more pricing instruments available to internalize the externalities of the different transport modes. Furthermore, this last result lends support to some opinions – such as those espoused in the OECD/ITF (2016) roundtable discussions – that tackling congestion and other externalities caused by ridesourcing services alone does not make much sense, given that this mode represents only a small fraction of total vehicle kilometres. Tackling the much greater negative externalities generated by more important transport modes, such as automobiles, should be the priority.

Sensitivity analysis of several assumptions and parameters do not significantly change our results. The exception is the value of the

[21] In the first-best scenario the optimal surcharge increases with respect to the relative ridesourcing/taxi share, while in the second-best scenario it decreases. This is due to the changes in the implicit substitution patterns with respect to the other modes. As the relative share increases, it also Increases the substitution between ridesourcing and taxis.

[22] Varying the $\alpha_{BPR}$ parameter has very minor effects on the results.

[23] In this sensitivity analysis, we do not re-calibrate de demand system, as it is a prospective analysis of what might happen given current preferences if policies are introduced to increase occupancy rates in the ridesourcing mode. We do reduce the fare and cost per passenger in the ridesourcing mode, since there are now more passengers per ride. We also increase the $K_r$ parameter in the calculation of $f_r$ in the BPR equation (24).

[24] We are assuming, however, that the pure preference parameter for ridesourcing, $\beta_r$, is the same for the different occupancy rates. This may not be a realistic assumption if the increase in the occupancy rate is achieved through new applications that offer shared rides among unrelated passengers (such as Uber Pool).

[25] We thank an anonymous referee for pointing this out to us.

**Table 9**
Sensitivity analysis of the optimal percentage surcharge for the ridesourcing mode for different initial modal share assumptions (%).

| | Initial ridesourcing share/taxi share | | |
|---|---|---|---|
| | **1.0 (base scenario)** | **2.0** | **3.0** |
| **First-best scenario** | 29.4% | 30.1% | 30.5% |
| **Second-best scenario** | 58.8% | 57.6% | 56.7% |

**Table 10**
Sensitivity analysis of the optimal percentage surcharge for the ridesourcing mode for different BRP function parameters (%).

| | $\beta_{BPR}$ | | |
|---|---|---|---|
| | **3** | **4 (base scenario)** | **5** |
| **First-best scenario** | 26.1% | 29.4% | 30.7% |
| **Second-best scenario** | 41.5% | 58.8% | 75.3% |

**Table 11**
Sensitivity analysis of the optimal percentage surcharge for the ridesourcing mode from changing average occupancy rate (%).

| | Occupancy rate (passengers/trip) on the ridesourcing mode | | |
|---|---|---|---|
| | **1.5 (base scenario)** | **2.0** | **2.5** |
| **First-best scenario** | 29.4% | 30.6% | 31.2% |
| **Second-best scenario** | 58.8% | 61.0% | 62.4% |

exponential parameter of the BPR function in a second-best scenario. The reason for this result is that in the first-best scenario, there are more instruments to internalize the negative congestion externality caused by each mode, reducing these externalities and thus making congestion less important for the determination of the optimal fare. In contrast, in a second-best scenario, there is only one policy instrument available, and congestion is larger than in the optimal first-best scenario. Thus, given the convexity of the BPR function, the optimal fare will be more sensitive to the effects of the congestion externality, which in turn will be affected by the parameters of the BPR function. The policy implication of this is that in a second-best environment, care must be taken to specify the BPR function correctly.

In this paper, we also examine the effects on optimal first-best and second-best fares from increasing the occupancy rates of the ridesourcing mode. Interestingly, the optimal first-best and second-best tax is proportionally higher as the occupancy rate increases, although the overall fare level per passenger is lower and the optimal use of ridesourcing services increases. The reason is that, while a higher occupancy rate does lower the per passenger congestion externality, it also lowers the per-passenger fare, incentivising the use of this mode. This second effect is more important in our application, calling for a slight increase in the optimal proportional surcharge (although not in the absolute per-passenger charge) when the average occupancy rate increases.

This last result is unexpected, and points to the importance of considering substitution effects among all modes when calculating optimal fares. It also has an interesting policy implication – namely, that the optimal tax rate on shared ridesourcing services is not necessarily lower (and may even be higher) than non-shared ridesourcing services.

The optimal ridesourcing tax from our model is larger than the 12% estimated by Gomez-Gelvez (2020) for the case of Bogotá. Part of this difference is due to his model assuming monopoly power for the ridesourcing application, and thus prices cost margin higher than in our application. The optimal tax in this context considers negative externalities but also a subsidy to reduce the inefficiency of the resulting market power price margin. The two effects counterbalance each other, resulting in a lower optimal tax compared to a case in which only externalities are considered.

We have shown in this paper how to calibrate and use a flexible demand model to estimate first-best and second-best tariffs for multimodal transport systems. This framework can be used in several different cities and contexts. Of particular importance in our application is the correct pricing of ridesourcing services. This has become an important issue in many cities, including Mexico City, Sao Paulo, Porto Alegre, Chicago, among others, which have introduced special charges or taxes in these new mobility services. If the empirical results for Santiago can be extrapolated to other Latin American metropolises such as Mexico City and Sao Paulo, our findings suggest that the optimal charge should be much higher than those introduced to date. The methodological approximation of this paper can be used to better inform such policy decisions.

Further research could extend the model to a long-run scenario in which bus and taxi capacity can be optimized. This would require introducing the impact of fares on supply, and thus on waiting and access times (the Mohring effect) in the optimization problem.

## CRediT authorship contribution statement

**Andrés Gómez-Lobo:** Conceptualization, Formal analysis, Methodology, Project administration, Resources, Software, Writing – original draft. **Alejandro Tirachini:** Supervision, Funding acquisition, Validation, Writing – review & editing. **Ignacio Gutierrez:**

Investigation, Data curation, Visualization.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### Appendix 1

To derive solve the maximization problem (9) subject to constraints (10a) to (10d), we start from the Lagrange function:

$$L=B(q_a,q_b,q_e,q_r)-q_a\bullet c_a-q_b\bullet c_b-q_e\bullet c_e-q_r\bullet c_r+\gamma_a\bullet\left(\frac{\partial B}{\partial q_a}-c_a\right)+\gamma_b\bullet\left(\frac{\partial B}{\partial q_b}-cu_b-\widetilde{\tau}_b\right)+\gamma_e\bullet\left(\frac{\partial B}{\partial q_e}-cu_e-\widetilde{\tau}_e\right)+\gamma_r\bullet\left(\frac{\partial B}{\partial q_r}-cu_r-\tau_r\right)$$

Taking the first order conditions with respect to each $q_i$, $\gamma_i$ and $\tau_r$, and using the notation $\frac{\partial^2 B}{\partial q_k \partial q_j}=B_{kj}$ and $\frac{\partial c_k}{\partial q_j}=c_{kj}$, we obtain:

$$\frac{\partial L}{\partial q_a}=B_a-c_a-q_a\bullet c_{aa}-q_b\bullet c_{ba}-q_e\bullet c_{ea}-q_r\bullet c_{ra}+\gamma_a\bullet(B_{aa}-c_{aa})+\gamma_b\bullet(B_{ba}-cu_{ba})+\gamma_e\bullet(B_{ea}-cu_{ea})+\gamma_r\bullet(B_{ra}-cu_{ra})=0 \tag{A.1}$$

$$\frac{\partial L}{\partial q_b}=B_b-c_b-q_a\bullet c_{ab}-q_b\bullet c_{bb}-q_e\bullet c_{eb}-q_r\bullet c_{rb}+\gamma_a\bullet(B_{ab}-c_{ab})+\gamma_b\bullet(B_{bb}-cu_{bb})+\gamma_e\bullet(B_{eb}-cu_{eb})+\gamma_r\bullet(B_{rb}-cu_{rb})=0 \tag{A.2}$$

$$\frac{\partial L}{\partial q_e}=B_e-c_e-q_a\bullet c_{ae}-q_b\bullet c_{be}-q_e\bullet c_{ee}-q_r\bullet c_{re}+\gamma_a\bullet(B_{ae}-c_{ae})+\gamma_b\bullet(B_{be}-cu_{be})+\gamma_e\bullet(B_{ee}-cu_{ee})+\gamma_r\bullet(B_{re}-cu_{re})=0 \tag{A.3}$$

$$\frac{\partial L}{\partial q_r}=B_r-c_r-q_a\bullet c_{ar}-q_b\bullet c_{br}-q_e\bullet c_{er}-q_r\bullet c_{rr}+\gamma_a\bullet(B_{ar}-c_{ar})+\gamma_b\bullet(B_{br}-cu_{br})+\gamma_e\bullet(B_{er}-cu_{er})+\gamma_r\bullet(B_{rr}-cu_{rr})=0 \tag{A.4}$$

$$\frac{\partial L}{\partial \gamma_a}=B_a-c_a=0 \tag{A.5}$$

$$\frac{\partial L}{\partial \gamma_b}=B_b-cu_b-\widetilde{\tau}_b=0 \tag{A.6}$$

$$\frac{\partial L}{\partial \gamma_e}=B_e-cu_e-\widetilde{\tau}_e=0 \tag{A.7}$$

$$\frac{\partial L}{\partial \gamma_r}=B_r-cu_r-\tau_r=0 \tag{A.8}$$

$$\frac{\partial L}{\partial \tau_r}=\gamma_r=0 \tag{A.9}$$

From (A.9) we know that the Lagrange multiplier associated with restriction (10.d) is zero. This simplifies the first order conditions (A.1) to (A.4) since the last term vanishes.

Replacing conditions (A.5) to (A.8) in (A.1) to (A.4) and using the definition for the average cost ($c_k = cu_k + co_k$) and marginal external cost ($mec_k$) from Eq. (6) above, conditions (12a) to (12d) are obtained.

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