Optimal regulation of oligopolistic markets under discrete choice models of demand

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Abstract

We propose a general framework to find optimal policies to regulate markets characterized by oligopolistic competition and in which consumers make a discrete choice among a finite set of alternatives. In our work, consumers are utility maximizers and are modelled according to random utility theory. Suppliers are modelled as profit maximizers, according to the traditional microeconomic treatment. Market competition is modelled as a non-cooperative game, for which a ε-equilibrium solution is sought. Finally, the regulator can affect the behavior of all other agents, for instance by giving subsidies or imposing taxes. In transport markets, these interventions might target specific alternatives, to reduce externalities such as congestion or emissions, or specific segments of the population, to achieve social welfare objectives. We present a mixed integer optimization model which can find optimal regulatory policies subject to market equilibrium, supplier profit maximization and consumer utility maximization constraints. We include this model in an algorithmic approach that finds ε-equilibrium solutions for the market. Finally, we report some preliminary numerical experiments which show the applicability of our approach on a transportation case study.

Keywords

regulation, competition, equilibrium, discrete choice modeling

1 Introduction

Public intervention in transport markets can be motivated by several phenomena. From an environmental perspective, it is acknowledged that transport markets are often the source of negative externalities, two very well-known cases of which are pollution and congestion. Policies to address these issues have been studied extensively in the literature for decades and they include road pricing (Button and Verhoef, 1998, Anas and Lindsey, 2011), taxes on fuel and vehicle purchase (Fullerton and West, 2002) and creation of low emission zones (De Borger and Proost, 2013, Cullinane and Bergqvist, 2014), among others. More recently, much attention has been given to the contribution of the transport sector to the increase of greenhouse gas emissions which are a leading cause of climate change (IPCC, 2014). Solutions that include a carbon tax are frequently proposed to reduce the negative impact of mobility on the environment. From a social perspective, a public entity might want to intervene in a transport market to incentivize mobility under certain circumstances. Indeed, improving mobility is often regarded as a means to increase economic output and enhance access to job opportunity or other activities from which the entirety or a part of the population can benefit. From an economic perspective, many transport markets, alike other network industries such as energy and telecommunications, are natural monopolies where suppliers benefit from large economies of scale and consumers place greater value on large networks than on small ones (Shapiro, 1998, Farsi *et al.*, 2007).

Public intervention can take many forms. In this work, we focus on regulation. Regulation is defined as an indirect public intervention aimed at orienting actors towards some welfare goals (Ponti, 2011). In this context, it can be seen as a middle way between a 'command and control' approach and a pure 'market competition' approach. Regulation can take various forms, which are generally framed within competition and antitrust laws that exist at local, national and international level and determine what a regulator can and cannot do to influence the market.

One common approach to regulation is the use of subsidization and taxation, which is the focus of this paper. In our work, we propose a framework to find optimal policies to regulate oligopolistic transport markets where demand is modeled at a disaggregate level. The use of models that capture complex disaggregate choice behavior allows the regulator to account for product differentiation and consumer behavioral heterogeneity at the individual level (Anderson *et al.*, 1992), and therefore to better tailor its policies.

The rest of the paper is organized as follows. Section 2 presents two choice-based mixed integer optimization models that optimize the decisions of the regulator of a competitive market. These models can be integrated in an algorithmic framework that finds ε-equilibrium solutions for the market. Section 3 illustrates some preliminary numerical experiments performed on a case studies representing an intercity travel market. Finally, Section 4 concludes the paper by mentioning the next steps of this ongoing research project.

2 Optimization models for regulated competition

We consider a regulated competitive market where a number of different products are offered to a population by two or more suppliers.

On the demand side, let N represent the set of heterogeneous consumers (or groups of consumers), who are assumed to be utility maximizers, and let I indicate the discrete and finite set of alternatives available in the market. Utility functions U_{in} are defined for each person $n \in N$ and alternative $i \in I$ in accordance with random utility theory, accounting for the socioeconomic characteristics and tastes of the individual and for the attributes of the alternative.

On the supply side, let K represent the set of suppliers and let $I_k \subset I$ indicate the subset of alternatives controlled by each supplier $k \in K$. We assume that each supplier solves a choice-based optimization problem, modeled in the form of a mixed integer optimization problem, aimed at finding the strategy that maximizes its profits. We define as $\mathcal{S}_k$ the set of strategies that can be selected by supplier k. A strategy consists in a vector (or bundle) of decisions, which we can separate into the vector p of all prices p_{in}, potentially differentiated for each (class of) consumer $n \in N$ and alternative $i \in I_k$, and a generic vector X of all other decisions.

The peculiarity of the proposed approach is the use of discrete choice models to inform the suppliers' strategic behaviour. Pacheco *et al.* (2017) and Bortolomiol *et al.* (2019) provide a more detailed discussion on the challenges associated with the integration of discrete choice models within mixed integer optimization models and within market equilibrium models and propose some methodologies to overcome them. In particular, Pacheco *et al.* (2017) present a MILP formulation which accommodates a disaggregate model of demand by relying on simulation to draw from the distribution of the error term of the utility functions of the consumers, while Bortolomiol *et al.* (2019) introduce an algorithmic framework to find ε-equilibrium solutions of oligopolistic markets where demand is modeled at the disaggregate level using discrete choice models.

In the rest of this section, we build on the aforementioned works to design a modeling framework that includes the role of the regulator. The regulator sets policies which influence the behaviour of the other agents, thus modifying the equilibrium outcome of the market. For the rest of the discussion, we concentrate our attention on pricing policies, i.e. subsidies and taxes, and we assume that a regulator has a maximum budget B which is available to finance these policies.

To formalize, let $I_s \subseteq I$ and $I_t \subseteq I$ represent the subsets of alternatives that are considered for subsidies and for taxes, respectively. For instance, when analyzing the opportunity of market intervention in an intercity travel market from an environmental perspective (see Section 3), subsidies could be considered for low-emission modes and taxes for high-emission mode. In other contexts, subsidies could be addressed to specific segments of the population (income-based, accessibility-based, etc.) with a social welfare perspective.

Under these assumptions, the value of the utility function U_{in} depends on the price p_{in} paid by consumer n for alternative i, which can be decomposed as

$$p_{in} = r_{in} + t_{in} - s_{in}, \tag{1}$$

where r_{in} is the revenue made by the supplier in case of purchase, t_{in} is the tax imposed by the regulator to the consumer, and s_{in} is the subsidy given by the regulator to the consumer. We can treat t_{in} and s_{in} as non-negative variables, which is useful to linearize the formulation, and impose that $s_{in} \cdot t_{in} = 0 \ \forall i \in I, \ \forall n \in N$. We also define the parameters M_s and M_t, which are upper bounds representing the maximum possible values for the subsidies and taxes and are used in the big-M constraints.

2.1 Regulator optimization

First, we look at the regulator optimization problem by assuming that all prices p_{in} decided by the suppliers are given. The goal of the model is to find an optimal solution with respect to the decision variables t_{in} and s_{in}, which affect the choices of the consumers. The resulting optimization model could be used as part of a numerical procedure to find a market equilibrium solution, such as the fixed-point iteration algorithm.

We remark that the modeling framework is very general and can accommodate various objective functions and problem-specific constraints. Those chosen here align with the case study proposed in Section 3.

We define the following additional notation. We use the simulation technique presented in Pacheco *et al.* (2017) to draw from the distribution of the error term of the utility function and define the binary variables P_{inr} as follows:

$$P_{inr} = \begin{cases} 1 & \text{if } U_{inr} = \max_{j \in I} U_{jnr}, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

that is, each consumer n deterministically chooses the alternative with the highest utility in each behavioural scenario r.

This is the resulting mixed integer optimization model:

$$\max \ \frac{1}{|N||R|} \sum_{i \in I_s} \sum_{n \in N} \sum_{r \in R} P_{inr} \tag{3}$$

s.t. Regulator constraints:

$$\sum_{n \in N} \sum_{r \in R} (\sum_{i \in I_t} \gamma_{inr} - \sum_{i \in I_s} \delta_{inr}) \leq B \tag{4}$$

$$0 \leq \delta_{inr} \leq M_s P_{inr} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{5}$$

$$s_{in} - M_s(1 - P_{inr}) \leq \delta_{inr} \leq s_i \qquad \forall i \in I, \forall n \in N, \forall r \in R \tag{6}$$

$$0 \leq \gamma_{inr} \leq M_t P_{inr} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{7}$$

$$t_{in} - M_t(1 - P_{inr}) \leq \gamma_{inr} \leq t_i \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{8}$$

Utility constraints:

$$U_{inr} = \beta_{p,in}(p_{in} + t_{in} - s_{in}) + q_{inr} + \xi_{inr} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{9}$$

$$U_{inr} \leq U_{nr} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{10}$$

$$U_{nr} \leq U_{inr} + M_U(1 - P_{inr}) \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{11}$$

$$\sum_{i \in I} P_{inr} = 1 \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{12}$$

$$P_{inr} \in \{0, 1\} \qquad \forall i \in I, \forall n \in N, \forall r \in R. \tag{13}$$

The objective function (3) maximizes the modal share of train alternatives, grouped in the set $I_s \subseteq I$.

Constraint (4) ensures that the budget of the regulator is respected. Constraints (5-8) linearize the product between the continuous subsidy/tax variables and the binary choice variables, through the auxiliary variables δ_{inr} and γ_{inr}. Constraints (9) define the deterministic utility functions for all alternatives, consumers and draws. Prices are fixed, subsidies and taxes are the endogenous variables, while everything else is grouped into the parameter q_{inr}. Constraints (10-12) ensure that in each behavioral scenario consumers deterministically choose the alternative yielding the highest utility. This is done by using the binary choice variables P_{inr} defined in (13).

2.2 Fixed-point MIP model with regulator

Model (3-13) does not include equilibrium conditions, since it takes the strategies of the suppliers as inputs of the problem. This means that it can only be used alongside other models.

Here we present a more complete model which considers the reaction of the suppliers, behaving as profit maximizing agents, to the policies of the regulator. This means that the output of the problem should be a state of the market in which no player has an incentive to unilaterally deviate. Similarly to Bortolomiol *et al.* (2019), we propose a mixed integer optimization model inspired by the fixed-point iteration algorithm, which returns an ε-equilibrium solution for problems where suppliers are assumed to have finite sets of strategies.

$$\max \ \frac{1}{|N||R|} \sum_{i \in I_s} \sum_{n \in N} \sum_{r \in R} P_{inr}{}' \tag{14}$$

$s.t.$ Regulator constraints:

$$\sum_{n \in N} \sum_{r \in R} (\sum_{i \in I_t} \gamma_{inr} - \sum_{i \in I_s} \delta_{inr}) \leq B \tag{15}$$

$$0 \leq \delta_{inr} \leq M_s P_{inr} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{16}$$

$$s_{in} - M_s(1 - P_{inr}) \leq \delta_{inr} \leq s_i \qquad \forall i \in I, \forall n \in N, \forall r \in R \tag{17}$$

$$0 \leq \gamma_{inr} \leq M_t P_{inr} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \tag{18}$$

$$t_{in} - M_t(1 - P_{inr}) \leq \gamma_{inr} \leq t_i \qquad \forall i \in I, \forall n \in N, \forall r \in R, \quad (19)$$

Equilibrium constraints:

$$\pi''_k \leq (1+\varepsilon)\pi'_k \qquad \forall k \in K, \quad (20)$$

Supplier constraints:

$$\sum_{s \in \mathcal{S}_k} x'_s = 1 \qquad \forall k \in K, \quad (21)$$

$$\sum_{s \in \mathcal{S}_k} x''_s = 1 \qquad \forall k \in K, \quad (22)$$

$$p'_i = \sum_{s \in \mathcal{S}_k} p_{is} x'_s \qquad \forall i \in I_k, \forall k \in K, \quad (23)$$

$$p''_i = \sum_{s \in \mathcal{S}_k} p_{is} x''_s \qquad \forall i \in I_k, \forall k \in K, \quad (24)$$

$$0 \leq \alpha_{inr}{}' \leq M_p P_{inr}{}' \qquad \forall i \in I, \forall n \in N, \forall r \in R, \quad (25)$$

$$p'_i - M_p(1 - P'_{inr}) \leq \alpha_{inr}{}' \leq p'_i \qquad \forall i \in I, \forall n \in N, \forall r \in R, \quad (26)$$

$$0 \leq \alpha_{inrs}{}'' \leq M_p P_{inrs}{}'' \qquad \forall i \in I, \forall n \in N, \forall r \in R, \forall k \in K, \forall s \in \mathcal{S}_k, \quad (27)$$

$$p''_i - M_p(1 - P''_{inrs}) \leq \alpha_{inrs}{}'' \leq p''_i \qquad \forall i \in I, \forall n \in N, \forall r \in R, \forall k \in K, \forall s \in \mathcal{S}_k, \quad (28)$$

$$\pi'_k = \frac{1}{|R|} \sum_{i \in I_k} \sum_{n \in N} \sum_{r \in R} \alpha'_{inr} \qquad \forall k \in K, \quad (29)$$

$$\pi''_{ks} = \frac{1}{|R|} \sum_{i \in I_k} \sum_{n \in N} \sum_{r \in R} \alpha''_{inrs} \qquad \forall k \in K, \forall s \in \mathcal{S}_k, \quad (30)$$

$$\pi''_{ks} \leq \pi''_k \qquad \forall k \in K, \forall s \in \mathcal{S}_k, \quad (31)$$

$$\pi''_k \leq \pi''_{ks} + M_\pi(1 - x''_s) \qquad \forall k \in K, \forall s \in \mathcal{S}_k, \quad (32)$$

Consumer constraints:

$$\sum_{i \in I} P_{inr}{}' = 1 \qquad \forall i \in I, \forall n \in N, \forall r \in R, \quad (33)$$

$$\sum_{i \in I} P_{inrs}{}'' = 1 \qquad \forall i \in I, \forall n \in N, \forall r \in R, \forall k \in K, \forall s \in \mathcal{S}_k, \quad (34)$$

$$U'_{inr} = \beta_{p,in}(p'_i + t_i - s_i) + q_{inr} + \xi_{inr} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \quad (35)$$

$$U'_{inr} \leq U'_{nr} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \quad (36)$$

$$U'_{nr} \leq U'_{inr} + M_U(1 - P'_{inr}) \qquad \forall i \in I, \forall n \in N, \forall r \in R, \quad (37)$$

$$U''_{inrs} = \beta_{p,in}(p''_i + t_i - s_i) + q_{inr} + \xi_{inr} \qquad \forall i \in I_k, \forall n \in N, \forall r \in R, \forall k \in K, \forall s \in \mathcal{S}_k, \quad (38)$$

$$U''_{inrs} = U'_{inr} \qquad \forall i \notin I_k, \forall n \in N, \forall r \in R, \forall k \in K, \forall s \in \mathcal{S}_k, \quad (39)$$

$$U''_{inrs} \leq U''_{nrs} \qquad \forall i \in I, \forall n \in N, \forall r \in R, \forall k \in K, \forall s \in \mathcal{S}_k, \quad (40)$$

$$U''_{nrs} \leq U''_{inrs} + M_U(1 - P''_{inrs}) \qquad \forall i \in I, \forall n \in N, \forall r \in R, \forall k \in K, \forall s \in \mathcal{S}_k. \quad (41)$$

The objective function (14) maximizes the modal share of train alternatives. Constraints (15-19) are as in (4-8). Constraints (20) are the ε-equilibrium conditions for the competitive market. Constraints (21-22) state that each supplier must select one strategy from its finite strategy set in both initial and final configurations. Constraints (23-24) derive the prices of the endogenous alternatives from the chosen strategies in both initial and final configurations. These equality constraints are included for the sake of readability. Constraints (25-28) linearize the product between the continuous price variables and the binary choice variables in the initial configuration and in all best response configurations, using the auxiliary variables $\alpha^{'}_{inr}$ and $\alpha^{''}_{inrs}$. Constraints (29-30) compute the profits of the suppliers in the initial configuration and in all final configurations. Constraints (31-32) state that in the final configuration each supplier selects the best response strategy to the initial configuration. Constraints (33-34) state that consumers deterministically choose one alternative in both initial and final configurations. Constraints (35-37) define the utilities and impose that consumers choose the alternative with the highest utility in the initial configuration. Constraints (38-41) impose the utility maximization principle in the best response configurations. Here, utilities are evaluated for all strategies of all suppliers. In each strategic scenario, the decisions of the optimizing supplier only affect the utility of its alternatives (38), while the utilities of the competitors' alternatives remain unchanged with respect to the initial configuration (39).

3 Numerical experiments

The models presented in Section 2 are integrated in the model-based algorithmic approach proposed by Bortolomiol *et al.* (2019) and tested on a case study about intercity mode and departure time choice for which a discrete choice model is derived from the literature.

3.1 Case study

Table 1 shows the supply data used for the tests. Travelers can choose among ten different alternative services to go from origin to destination within a given time period. Car, air and intercity train alternatives are modelled as exogenous options, i.e. all their attributes are assumed to be parameters of the problem, while high-speed rail alternatives are modelled endogenously, i.e. the two competing operators strategically choose their prices in response to the conditions of the market. The attributes that are included in the customer utility functions for the different alternatives are cost, in-vehicle travel time,

Alternative	0	1	2	3	4	5	6	7	8	9
Mode	Car	Air	Air	IC	HSR	HSR	HSR	HSR	HSR	HSR
Endogenous	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Operator	-	-	-	-	1	1	1	2	2	2
Dep	-	7:10	8:10	2:00	5:45	6:15	6:45	5:35	6:05	6:35
Arr	-	8:20	9:20	10:00	8:45	9:15	9:45	8:55	9:25	9:55
TT	6h	1h10'	1h10'	8h	3h	3h	3h	3h20'	3h20'	3h20'
WT	-	1h	1h	-	-	-	-	-	-	-
Access	-	30-60'	30-60'	0-60'	0-60'	0-60'	0-60'	0-60'	0-60'	0-60'
Egress	-	30-60'	30-60'	0-30'	0-30'	0-30'	0-30'	0-30'	0-30'	0-30'
Price	100 €	60 €	60 €	30 €	p_4	p_5	p_6	p_7	p_8	p_9

Table 1: Attributes of all scheduled services for the analyzed problem instance.

β		Business travelers		Other purpose travelers	
μ_{Air}		1.086		1.106	
μ_{HSR1}		1.190		1.333	
μ_{HSR2}		1.134		1.299	
Travel time (min)		-0.0133		-0.0054	
Access/egress time (min)		-0.00555		-0.0103	
Early schedule delay (min)		-0.00188		-0.00677	
Late schedule delay (min)		-0.0130		-0.00617	
Dummy male (for car) (1/0)		1.400		0.550	
	Reimbursed	High income	Low income	High income	Low income
Cost car (euro)	-0.0222*	-0.0296*	-0.0527	-0.0228*	-0.0405
Cost Air (euro)	-0.0109	-0.0113*	-0.0201	-0.0109*	-0.0194
Cost IC (euro)	-0.0158	-0.0212*	-0.0377	-0.0097*	-0.0172
Cost HSR (euro)	-0.0120	-0.0160*	-0.0284	-0.0144*	-0.0256

Table 2: Model parameters derived from Cascetta and Coppola (2012). [1]

waiting time, access time to and egress time from the terminal, early or late arrival at destination with respect to the desired arrival time of the traveler.

On the demand modeling side, Table 2 reports the discrete choice parameters used in the experiments, which have been derived from a nested logit model estimation presented in Cascetta and Coppola (2012), where two separate models are developed for business and non-business travelers for the Italian intercity travel market. The μ coefficients capture the degree of similarity of alternatives belonging to each of the three nests. The mode-specific cost parameters yield different price sensitivities for non-business, non-reimbursed business and reimbursed business travelers. In order to analyze various policy making scenarios and explore the features of our modeling framework, we inserted an additional distinction between low and high income travelers. Table 3 reports the resulting values of travel time for the different groups of travelers.

[1] Non-starred values are taken as such from Cascetta and Coppola (2012). The $\beta_{cost_{car}}$ parameter for reimbursed business customers is derived by assuming that the ratio between the values of travel time of reimbursed and non-reimbursed business travelers by car is the same as by train. We have introduced an additional distinction between high income and low income travelers. This is done in order to test scenarios where government intervention is targeted to specific segments of the population. We have arbitrarily assumed that β_{cost} parameters of non-reimbursed business travelers and of other

Value of Travel Time	Reimbursed	High income	Low income	High income	Low income
Car (euro/h)	35.88*	26.95*	15.14	14.24*	8.00
Air (euro/h)	73.21	70.67*	39.70	29.73*	16.70
IC (euro/h)	50.51	37.68*	21.17	33.54*	18.84
HSR (euro/h)	66.50	50.02*	28.10	22.53*	12.66

Table 3: Values of travel time

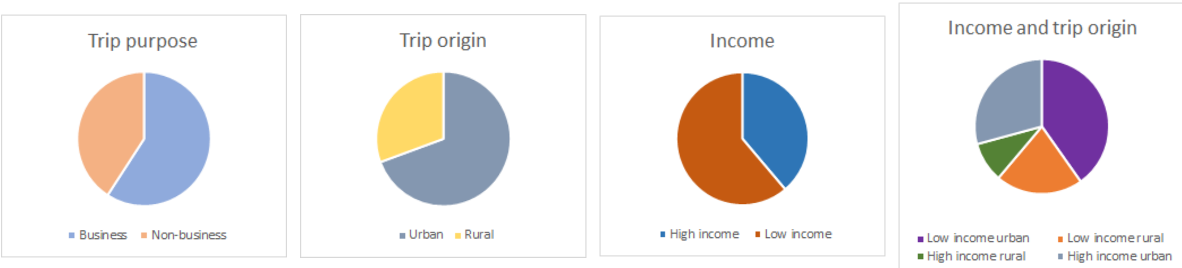


Figure 1: Aggregate data for four different socioeconomic characteristics.

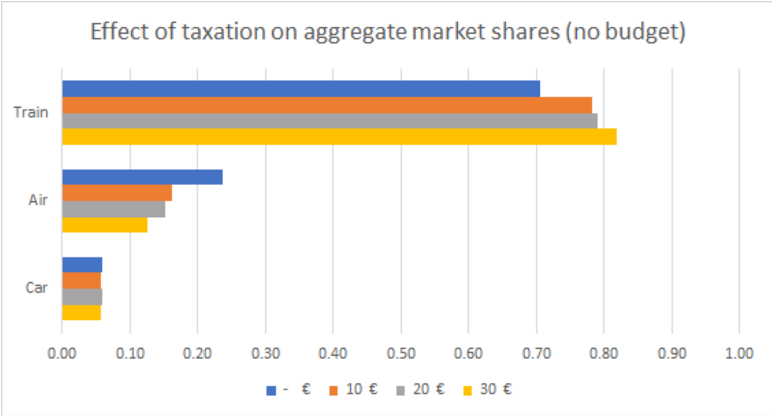
For these experiments, we generate a synthetic population of 500 travelers for each of the two instances. Individuals have a trip purpose (business or other), specific origin (urban or rural) and destination locations which lead to different access and egress times to and from terminals, an income level (high or low), and a desired arrival time at destination. Aggregate values for these socioeconomic characteristics are shown in Figure 1.

We remark that the dataset used for the experiments and the derived results are hypothetical and do not represent real scenarios that are related to choices made by existing high-speed rail operators.

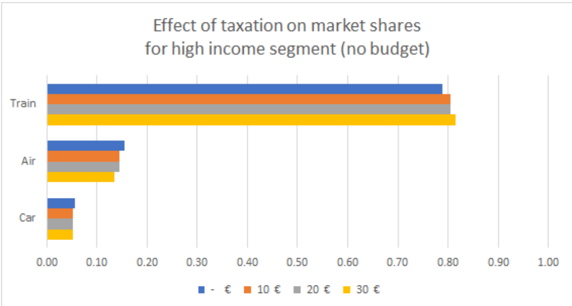
3.2 Tests

The design of the testing scenarios was done in order to answer open questions in the following areas: (i) demand analysis, i.e. the effects of taxes and subsidies on the choices and the utilities for the population as a whole and for specific segments; (ii) competition analysis, i.e. how the supply pricing strategies and the resulting profits are affected by regulation; (iii) environmental analysis, i.e. the values of marginal abatement costs in different policy scenarios and the results of a cost-benefit analysis that weighs the monetized benefits of reduced emissions against the budget required to achieve such reduction. Not all these questions have been answered. Here we only report the results of

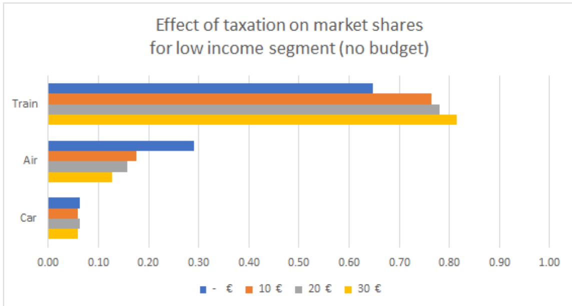
travelers from Cascetta and Coppola (2012) apply to our low income segment of the population. β_{cost} parameters for high income customers are derived by assuming that the ratio between the values of travel time of high income and low income customers is the same as in the SAMPERS long-distance model developed in Sweden and reported in Börjesson (2014).



(a) Aggregate market shares



(b) High income segment

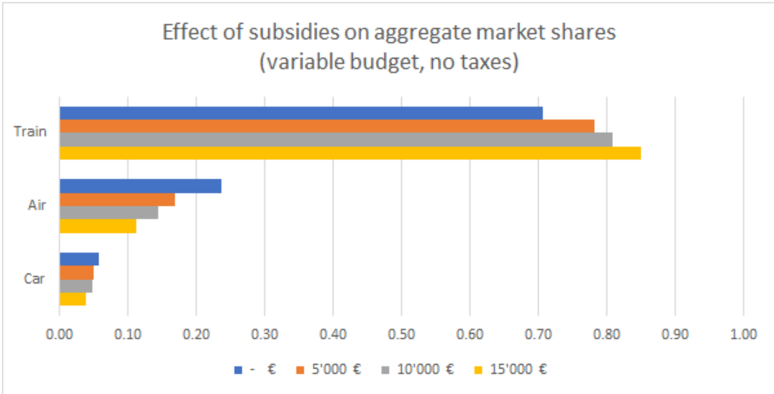


(c) Low income segment

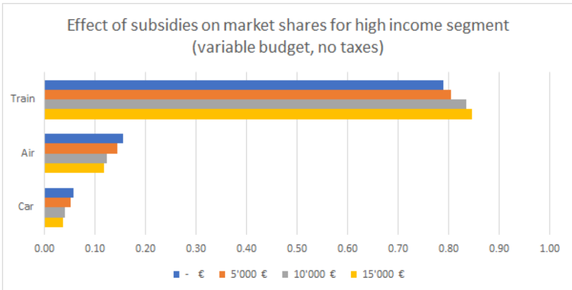
Figure 2: Revenue recycling with different taxation caps

some preliminary experiments aimed at exploring the features of the models presented in Section 2.

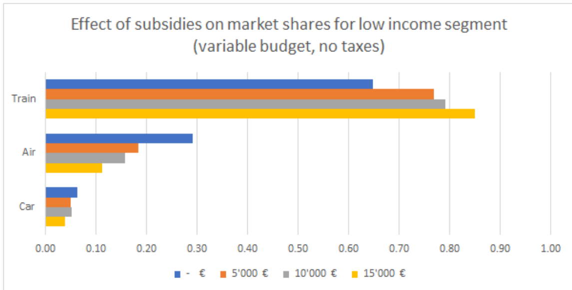
First, we examine a scenario where the regulator does not have any budget available to implement its policies. As a consequence, the subsidies that are handed out to the customers who choose a green mode of transport (in this case the train) must be collected from those who select a more polluting alternative (in this case the plane), following a revenue recycling approach. Figure 2(a) shows the aggregate market shares at equilibrium for four different tax caps on air ticket sales, i.e. 0 € (unregulated market), 10 €, 20 € and 30 €. As expected, higher tax caps drive more people away from flying and into the subsidized train alternatives. Figures 2(b) and 2(c) show that the modal shift is more evident among low income people who are more price sensitive. In this specific case, high income customers show a higher preference towards high-speed rail alternatives in the unregulated market, which might lead to the assumption that, as a group, they can further benefit from the subsidization of those services. Contrarily, more low income customers might face a decrease of the utility of their selected choice due to the flight taxes that are forcing them to select a more expensive alternative in the regulated market. However, deeper analyses should be conducted to quantify the social impact of regulation in terms



(a) Aggregate market shares



(b) High income segment



(c) Low income segment

Figure 3: Subsidization with different budget caps

of customer utilities.

Then, we test a scenario where the regulator does not impose taxes. Instead, it finances subsidies with exogenous budgets, i.e. 0 € (unregulated market), 5000 € (average of 10 € per person on the market), 10000 € and 15000 €. Figures 3(a), 3(b) and and 3(c) show similar patterns to the previous case, with higher modal shift on the low income segment of the population, which this time is not touched by direct taxation.

The equilibrium solutions for different regulated market scenarios result in different outcomes for the suppliers. Figure 4 shows the profits obtained by the two high-speed rail operators both in the scenario with revenue recycling and in that where subsidies are financed through an exogenous budget.

4 Conclusion

In this paper, we introduce a choice-based optimization model which exploits discrete choice models of demand to find optimal policies to regulate oligopolistic markets. Us-

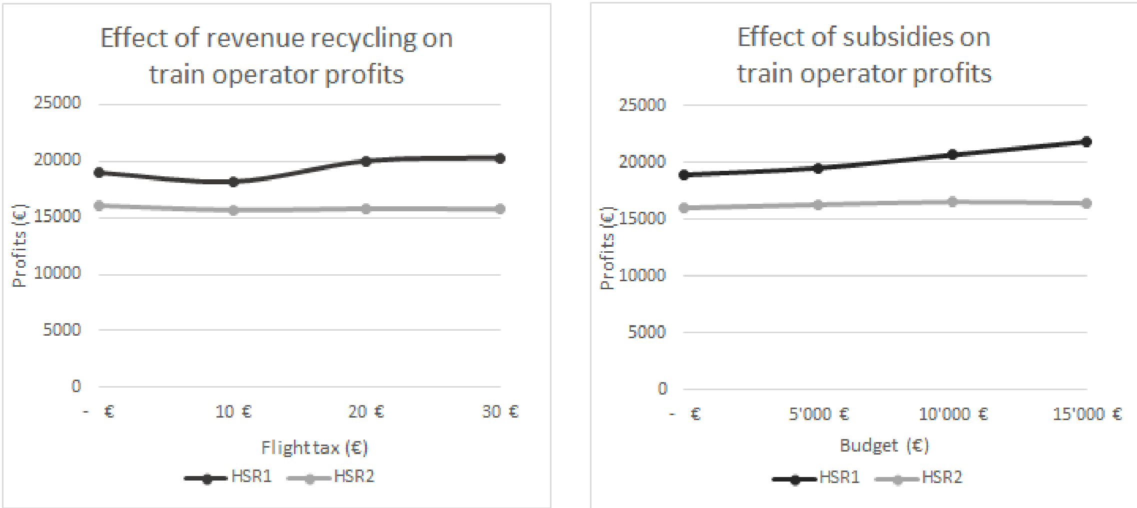


Figure 4: Profits

ing a disaggregate representation of demand that accounts for demand heterogeneity allows to accurately model supply-demand interactions. This model is included in a model-based algorithmic approach that finds ε-equilibrium solutions for the given market. The algorithmic approach is applied to a transportation case study about an intercity travel market. Preliminary numerical experiments show that the framework can provide insights at both demand and supply levels and can inform policy-making decisions that aim at maximizing welfare by reducing the negative externalities associated with many transportation markets.

The framework we propose is very general. Depending on political opportunity and acceptance, there could be many possible policies that leverage on subsidization or taxation to regulate a transportation market to lead to desirable outcomes from economic, social and environmental points of view. In the next phases of this research, we are planning to investigate the following cases: (i) the regulator implements policies targeted to specific market segments that take into account the heterogeneity of the population; (ii) the objective function of the regulator reproduces a comprehensive cost-benefit analysis which includes the budget spent by the regulator, the producer and consumer surplus on the operator and traveler side, respectively, and the monetary cost of carbon emissions.

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