Welfare Implications of Subsidy Design with Intertemporal Price Discrimination*

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Abstract

I study the impact of different subsidy designs for consumers in settings where firms have market power and exercise intertemporal price discrimination, such as airlines and hotels. Certain subsidy designs can steer demand toward high-priced products, increasing government spending as an unintended consequence. Using as a case study the subsidies for residents in remote territories in the Spanish airline industry, I develop a dynamic discrete choice model and estimate the demand parameters of forward-looking consumers who decide on the timing of their purchases. Combining the estimated demand parameters with a supply model in which multiproduct firms choose prices in every period, I perform a counterfactual analysis to evaluate the impact of changing the subsidy design from the current *ad valorem* design to a unit design. I show that accounting for price discrimination is important when analyzing the question of unit versus *ad valorem* designs. I also show that changing to a unit design would generate almost 15% savings for the government due to the shift in consumption patterns toward cheaper options.

Keywords: Subsidy design, airline industry, dynamic discrete choice estimation, zero purchases.
JEL Codes: D43, C35, L13, L93, H21, H25

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1 Introduction

Government intervention through subsidies is pervasive across industries, typically with the goal of ensuring access to essential goods that are provided in market settings. Examples range from housing and health to transportation. Yet, as basic economic theory emphasizes, intervention may distort equilibrium outcomes; moreover, the opportunity cost of public funds matters for policy design. A natural question is therefore how different subsidy designs perform in achieving a given access objective while minimizing distortions and expenditure. A large literature studies these trade-offs under uniform pricing (e.g., Suits and Musgrave, 1953; Auerbach and Hines, 2001), but much less is known about settings in which firms engage in price discrimination. Recent theory highlights that incidence can be markedly different when firms price-discriminate, and that policy may need to be tailored to the relevant margin of discrimination (D'Annunzio and Russo, 2022; see also Weyl and Fabinger, 2013; Adachi and Fabinger, 2021).

This paper analyzes the welfare consequences of two common subsidy designs in the presence of intertemporal price discrimination:

1. **Ad valorem subsidy:** the subsidy is a percentage of the posted price.
2. **Unit (specific) subsidy:** the subsidy is a fixed amount per unit consumed.

In the standard uniform-pricing benchmark, the two instruments can be equivalent in perfectly competitive markets, while under imperfect competition their relative performance depends on pass-through and markups (Suits and Musgrave, 1953; Auerbach and Hines, 2001). When firms price discriminate, however, the interaction between the instrument and the dimension of discrimination becomes central. In our setting the discriminating dimension is *time of purchase*: prices vary depending on when a good is bought. The interaction between price discrimination and subsidy design is important because an *ad valorem* subsidy both (i) attenuates effective price sensitivity by scaling the price coefficient and (ii) mechanically raises the monetary value of the transfer in high-price periods. Building on the insights in D'Annunzio and Russo (2022)—who show that welfare-enhancing taxation under price discrimination may require policies that "discriminate" across purchase types—this paper provides an empirical quantification of these mechanisms in a dynamic demand industry (the air travel industry), with forward-looking consumers and oligopolistic multiproduct firms.

The specific empirical setting is the Spanish air transportation market, where residents of the Canary Islands, Balearic Islands, Ceuta and Melilla receive a 75% discount on domestic airfare—an *ad valorem* consumer subsidy. The stated objective is to guarantee access and foster territorial cohesion. Similar programs exist in other European countries, sometimes via supply-side PSOs rather than consumer-side transfers. While the program arguably achieves its policy goal of securing connectivity for these territories, it also raises concerns about fiscal cost and price responses. Mechanically, an *ad valorem* discount reduces observed price elasticities, and there is evidence of higher fares on subsidized routes (Calzada and Fageda, 2012; Fageda et al., 2017; CNMC, 2020; AIReF, 2021). Recent press reports indicate additional budgetary pressure as the program has expanded[1]. These facts motivate reassessing the design through the lens of intertemporal price discrimination.

A key point is that conventional uniform-price analyses may understate fiscal impacts if they ignore how the instrument reshapes *when* purchases occur across the booking horizon. Using the running example of the airline industry, with rising price paths, an *ad valorem* subsidy shifts demand toward the most expensive periods: because the transfer is proportional to price, it grows precisely where fares are highest, and—by shrinking the effective price coefficient—it dulls incentives to buy early. In contrast, a unit subsidy keeps the marginal transfer constant across time and leaves the price coefficient unaffected. One can expand this logic to other settings with second-degree price discrimination, such as industries with different quality versions of goods. In such settings, an *ad valorem* subsidy design would steer consumers toward high-quality, high-price variants. If the policy goal of a subsidy is to guarantee access to a certain good, but not necessarily to the high-quality version of a good, then the impact of each design becomes relevant in the presence of price discrimination.

This mechanism is relevant beyond air travel. In markets for durable or perishable goods where timing or quality tiers interact with market power—such as electric vehicles (EVs) with rebates or tax credits—subsidy design determines both pass-through and which product/period margins are favored. Recent work documents how attribute-based EV subsidies interact with market power and pass-through (Barwick, Kwon, and Li, 2024), and how consumer responses vary across income groups under EV incentive programs (Muehlegger and Rapson, 2022). The contribution of this paper complements this literature by emphasizing the *intertemporal* dimension: we show that when firms can price discriminate over time, an *ad valorem* design can inadvertently concentrate purchases in high-price states, inflating program costs, whereas a unit design can achieve similar access at lower fiscal expense by realigning incentives toward earlier, cheaper purchases. The analysis in this paper is also relevant beyond industries with multiperiod

[1] https://cincodias.elpais.com/companias/2025-04-22/el-gobierno-busca-apoyos-para-tapar-el-agujero-de-319-millones-por-los-vuelos-subvencionados-a-las-islas.html (in Spanish)

pricing, since price discrimination occurs also in industries like the health industry, education. This paper shows that when a government wants to subsidize consumers to secure access in those industries, it should take into account price discrimination and how the design of the subsidy may steer consumers towards high quality version and inflate the subsidy cost beyond what it is necessary.

Using rich transaction-level data from Spain, I develop and estimate a dynamic discrete choice model of forward-looking subsidized consumers who choose both *whether* and *when* to purchase. I combine this with a multiproduct oligopoly model of intertemporal pricing and use the estimated demand to quantify how switching from an *ad valorem* to a unit subsidy changes purchasing patterns, prices, welfare, and government expenditure. The analysis shows that accounting for intertemporal price discrimination is essential for evaluating unit versus *ad valorem* designs and for understanding the distributional and fiscal consequences of consumer subsidies. I also show that changing from the observed *ad valorem* to a unit design would generate almost a 15% reduction in the total spending in the program, while keeping total demand constant. This is due to the change in demand patterns after the subsidy change: a large share of purchases happens in earlier periods. Additionally, the share of low cost carriers increases. Profits of all airlines decreases whereas high price sensitivity consumers are better off despite consuming worse quality products.

Literature Review

This project contributes to three main strands of the literature. First, it relates to work on the welfare effects of taxes and subsidies under imperfect competition. Classic analyses compare unit and *ad valorem* instruments (Suits and Musgrave, 1953; Auerbach and Hines, 2001), while more recent theory develops general pass-through tools and incidence formulas for market power (Weyl and Fabinger, 2013; Adachi and Fabinger, 2021). Within this strand, a central insight for the present paper comes from D'Annunzio and Russo (2022), who show that when firms price discriminate, welfare-enhancing taxation may itself need to "discriminate" across the relevant types. Their results imply that the interaction between an instrument and the *dimension of discrimination* (e.g., timing, versioning, or buyer type) can overturn standard uniform-pricing conclusions. I build on this logic by focusing on *intertemporal* price discrimination: when prices rise with departure proximity, an *ad valorem* subsidy simultaneously scales down effective price sensitivity and magnifies the transfer in high-price periods, whereas a unit subsidy keeps the transfer constant over time. The paper provides an empirical assessment of these mechanisms and quantifies the fiscal and welfare implications of alternative designs in a market with forward-looking consumers and oligopolistic multiproduct firms.

Second, the paper connects to the literature on subsidies in air transportation. Calzada and Fageda (2012) document higher fares on routes with resident discounts; Fageda, Jiménez and Valido (2017) show that price effects arise on routes where subsidies discriminate between residents and non-residents, while Fageda et al. (2016) find limited average differences in some Spanish contexts. The present study contributes by structurally estimating demand for resident consumers on subsidized Spanish routes, allowing for forward-looking purchase timing and heterogeneity by income group, and by conducting an ex ante policy evaluation that compares the current *ad valorem* design to a unit subsidy while holding aggregate access constant.

Third, the paper contributes to empirical work on airline pricing with dynamic demand and capacity considerations. Closest to this project is Lazarev (2025), who models forward-looking consumers and studies cancellation policies. Related contributions include Williams (2022) and Betancourt et al. (2024), who analyze dynamic pricing and capacity constraints. Relative to these papers, my focus is on the interaction between *subsidy design* and intertemporal price discrimination, and on how this interaction shapes purchase timing, incidence, and program cost.

Finally, the paper relates to the design of consumer subsidies in markets with durability/perishability and product or quality ladders, including electric vehicles (EVs). Recent work studies how attribute-based subsidies interact with market power and pass-through (Barwick, Kwon, and Li, 2024) and how incentives differentially affect adoption across income groups (Muehlegger and Rapson, 2022). My contribution is complementary: I emphasize the *timing* margin intrinsic to intertemporal price discrimination. When the transfer is *ad valorem*, beneficiaries are nudged toward high-price states (late purchases or high-version products), which can inflate fiscal outlays even if access targets are met; a unit design realigns incentives toward earlier, cheaper purchases. The mechanisms I document for airlines apply to other durable/perishable settings in which quality or timing interacts with market power.

Relation to dynamic discrete choice estimation. On the methodological side, the paper draws on the dynamic discrete choice (DDC) literature. Rust (1987) pioneered the structural estimation of Markov decision processes via nested fixed-point methods, providing conditions for identification and a practical algorithm for solving dynamic programming problems in demand contexts. Hotz and Miller (1993) introduced the conditional choice probability (CCP) approach, which inverts observed choice probabilities to recover value function differences, enabling more tractable estimation in dynamic settings. I adopt a CCP-based strategy to model forward-looking purchase timing and combine it with recent techniques for zero market shares in differentiated-product demand. Specifically, I address zero purchases at the product–market–period level using a selection step and correction following Dubé, Hortaçsu, and Joo (2020), then estimate a BLP-style random-coefficients model on the selected set. This integration allows consistent estimation of dynamic demand with realistic sparsity in observed purchases and is tailored to settings with intertemporal price discrimination.

Structure of the Paper

The remainder of the paper proceeds as follows. Section 2 describes the institutional background of Spain's resident airfare discounts and the datasets used. Section 3 develops the consumer model with forward-looking subsidized residents and tourists; residents choose both *whether* and *when* to buy along the booking horizon. Estimation leverages the Hotz–Miller (1993) CCP framework to express continuation values and derive period-specific purchase probabilities. Section 4 details the empirical strategy: a two-stage approach that (i) models selection into strictly positive purchases at the product–market–period level to handle zero shares, and (ii) estimates a random-coefficients logit using BLP-style moments with instrumental variables, incorporating the selection correction in the mean utility. Section 5 presents the supply side: a multiproduct oligopoly with intertemporal pricing; observed prices and estimated demand are used to back out marginal costs and to characterize equilibrium pricing across periods. Section 6 conducts the counterfactual policy analysis, recalculating equilibrium under a unit (specific) subsidy calibrated to preserve aggregate access, and reports impacts on purchase timing, government expenditure, consumer surplus by group, and firm profits. Section 7 concludes by discussing implications for the design of consumer subsidies in markets with intertemporal price discrimination and for related settings such as EV adoption.

2 Intuition of Unit vs. *ad valorem* and Price Discrimination

Consider a monopolist facing two consumer groups: high willingness-to-pay (h) and low willingness-to-pay (l). Consumers of type $i \in \{h, l\}$ have linear demand

$$q_i = a - b_i p,$$

with $b_l > b_h$ so that the low-WTP group is more price sensitive (more elastic). A useful interpretation in intertemporal settings is: type h corresponds to late buyers (inelastic), while type l corresponds to early buyers (elastic).

Suppose there is an *ad valorem* subsidy $\tau \in (0,1)$ to consumers. Under an *ad valorem* subsidy, the posted price is p and the consumer pays $(1-\tau)p$; under a unit (specific) subsidy T, the consumer pays $p-T$. The firm's marginal cost is constant at c.

Price discrimination vs. uniform pricing. We compare two pricing regimes: (i) price discrimination (PD), where the monopolist sets a separate price p_i for each type i; and (ii) uniform pricing (UP), where the monopolist sets a single price $\bar{p}$ for both types. For the sake of the argument, I assume the monopolist that price discriminates can perfectly screen types and every consumer buys the bundle designed for them. Under price discrimination, with linear demand and constant marginal cost, the profit-maximizing posted prices under an *ad valorem* subsidy τ and a unit subsidy T are

$$p_i^{AV} = \frac{a}{2b_i(1-\tau)} + \frac{c}{2}, \qquad p_i^U = \frac{a}{2b_i} + \frac{c+T}{2}.$$

Under uniform pricing, the monopolist can choose whether to serve both types at $\bar{p} = \frac{2a}{2(b_h+b_l)(1-\tau)} + \frac{c}{2}$, or serve only high types at the p_h^{AV} defined above.

For any of the two pricing regimes, we can find the unit subsidy which keeps demand equal to the quantity consumed under an *ad valorem* subsidy; equating $q_i^U = q_i^{AV}$ for all i gives the *equivalent* unit subsidy

$$T^{eq} = \tau c.$$

Thus, with linear demand and constant c, a unit subsidy $T^{eq} = \tau c$ replicates the distribution of quantities across types that arises under the *ad valorem* design. This quantity equivalence holds both under price discrimination (type-by-type) and under uniform pricing (in aggregate). It follows immediately that the *ad valorem* and unit designs imply different posted-price pass-through with respect to τ:

$$\frac{\partial p_i^{AV}}{\partial \tau} = \frac{a}{2b_i(1-\tau)^2}, \qquad \frac{\partial p_i^U}{\partial \tau} = \frac{1}{2}\frac{\partial T}{\partial \tau}.$$

If we choose the unit subsidy to match quantities across designs (see below), the equilibrium "equivalent" unit subsidy is $T^{eq} = \tau c$, so $\partial T/\partial \tau = c$ and thus

$$\frac{\partial p_i^U}{\partial \tau} = \frac{c}{2}.$$

Two immediate implications follow.

- **Ad valorem pass-through depends on demand primitives and type.** Under *ad valorem*, pass-through into posted prices rises as demand becomes less elastic (smaller b_i): $\partial p_i^{AV}/\partial\tau$ is larger for the high-WTP (late) type. With price discrimination, this amplifies type-specific price responses.

- **Unit pass-through is independent of the pricing regime.** With $T^{eq} = \tau c$, posted-price pass-through under the unit design is $\partial p_i^U/\partial\tau = c/2$ for each type i, regardless of whether the firm price discriminates or sets a uniform price. By contrast, *ad valorem* pass-through varies by type and depends on (a, b_i, τ).

Distributional incidence and increasing marginal cost

Under the linear–constant-c benchmark with $T^{eq} = \tau c$, the quantities by type are the same under *ad valorem* and unit designs, but the distribution of government spending differs: under *ad valorem*, each unit to type i receives a transfer τp_i, which is larger for the high-WTP (late) type since $p_h > p_l$; under the unit design, each unit receives the same τc. Thus, even when quantities coincide, *ad valorem* payments are more concentrated on high-price (late) purchases.

Once we relax the constant-c assumption and allow marginal cost to be increasing in quantity , a single unit subsidy T that preserves aggregate quantity will generally reallocate consumption toward the more elastic (early) type and away from the inelastic (late) type. This mirrors the airline setting where the relevant economic marginal cost is the opportunity cost of depleting remaining capacity: as spare capacity shrinks, the shadow cost rises, making late-period units more expensive to serve (e.g., Williams (2022), Betancourt et al. (2024)). In such environments, the unit design restores effective price sensitivity (by not scaling the price coefficient) and reduces the late-period tilt that *ad valorem* subsidies create.

Policy trade-off

The core trade-off is between (i) *steering* purchases toward earlier, cheaper products/periods (unit design) and (ii) *guaranteeing* minimum consumption across varieties or time states (where *ad valorem* acts like insurance against high prices but inflates fiscal outlays in high-price states). In markets with intertemporal price discrimination, unit subsidies achieve access targets at lower fiscal cost by preserving price sensitivity and dampening incentives to delay into expensive late-period purchases.

3 Institutional Setting and Data

In this section, I describe in further detail the subsidy program present in the Spanish air travel industry. I also explain the data observed in this industry and the information it contains that allows me to answer the research question.

3.1 Current design of price discounts in air transportation in Spain

Price discounts in air transportation in Spain for residents in remote territories are regulated by Spanish law as follows.[2] As mentioned earlier, the current design is an *ad valorem* subsidy. Residents in the Canary Islands, the Balearic Islands, Ceuta, and Melilla are entitled to these price discounts for trips between these remote territories and other airports in national territory, or trips within the remote territories. Since July 2018, the discount percentage has been set at 75% of the ticket fare. Airlines manage this subsidy, meaning consumers are charged the discounted price, and airlines request the total discount applied throughout the year from the Spanish government. Therefore, resident consumers face the effective price[3] when deciding on a purchase.

This subsidy was introduced in the 1960s, initially only for residents in the Canary Islands. Over time, the amount of the discount has increased from 12% to 75%. With the arrival of democracy, the Balearic Islands, Ceuta, and Melilla were included in the program. The discount amount increased to 50% and then to 75% in July 2017 for inter-island flights and July 2018 for flights between remote territories and mainland Spain. Similar programs exist in other EU member states, such as Portugal, Italy, France, and the UK, aimed at facilitating access to essential goods for citizens in remote territories. Absent such subsidies, airlines might offer less frequent, more expensive services, or no service at all, due to low demand and high costs on these routes (Calzada, 2012).

3.2 Data

I use two datasets for the empirical analysis. The main dataset is the transactions dataset from the *Dirección General de Aviación Civil* (hereinafter, DGAC), a Directorate-General within the Spanish Ministry of Development, which is the government institution in charge of managing the price-discount program in air transportation. This dataset contains information on all airplane tickets that were purchased with a price discount between July 1, 2015 and July 1, 2019, i.e., all tickets purchased by consumers whose residence is in the Canary or the Balearic Islands for flights with origin or destination in one of these territories, within Spain. For each plane ticket I observe: **route**, **date and time of flight**, **date of purchase**, **price of purchase**, and **consumer identifier**. Observing the date of purchase allows me to

[2] Real Decreto 1316/2001, de 30 de noviembre, por el que se regula la bonificación en las tarifas de los servicios regulares de transporte aéreo y marítimo para los residentes en las Comunidades Autónomas de Canarias y las Illes Balears y en las Ciudades de Ceuta y Melilla.

[3] Effective price = price $\times$ (1 - discount).

compute how many days in advance each ticket was bought. To convey the richness and size of the data, looking at a selection of the largest routes between the Canary and Balearic Islands and mainland Spain,[4] the data have the following characteristics:

Data Characteristics			
Year	**Observations**	**Consumers**	**Flights**
2015	2,567,687	64,453	205,550
2016	5,489,344	129,607	407,091
2017	6,027,538	132,894	446,544
2018	6,958,893	149,330	551,028
2019	4,318,394	87,697	365,116

As can be seen in the table above, there is a very large number of observations every year. Crucially, there is also a large number of consumers observed purchasing tickets across many flights. Since the number of observations per year is larger than the number of consumers, this means that I observe the same consumer making repeated choices.

The second dataset contains the universe of flights in Spanish territory during the same time span. The observation level is the flight, and the crucial information it contains is aircraft capacity and the number of passengers at departure time for each flight. This second dataset is provided by AENA,[5] the airport operator. By combining the two datasets at the flight level, I can obtain the number of non-subsidized passengers on every flight as the subtraction of total passengers and the total number of tickets purchased by subsidized consumers on each flight, obtained from the first dataset. This is essential information because in my first dataset I only observe purchases made by subsidized consumers. Therefore, for non-subsidized consumers I observe the total number of passengers per flight, but not the timing of their purchases. This will require some assumptions in the estimation and counterfactual sections of the paper, which I explain in the corresponding sections.

Motivating Evidence

Beyond the literature and policy and press reports mentioned in the previous section, I also show evidence of the large increase in the cost of the subsidy program leveraging the last change in the subsidy rate,

[4]Gran Canaria–Madrid, Tenerife–Madrid, Mallorca–Madrid, Barcelona–Gran Canaria, Barcelona–Tenerife, Barcelona–Mallorca, in both directions.

[5]AENA is the public enterprise in charge of operating airports in Spain.

which I observe in the data. Using data on purchases made by subsidized consumers and the change in the subsidy rate from 50% to 75% in summer 2018, I now show motivating evidence of the effects of the subsidy program on intertemporal price discrimination and on consumer purchasing patterns. First, in Figure 1, I show how the total cost of the subsidy program spiked after this subsidy-rate increase. As seen in the graph, the increase in the total cost for the year after the increase (30 million €) equals the increase in the three years preceding the subsidy change.

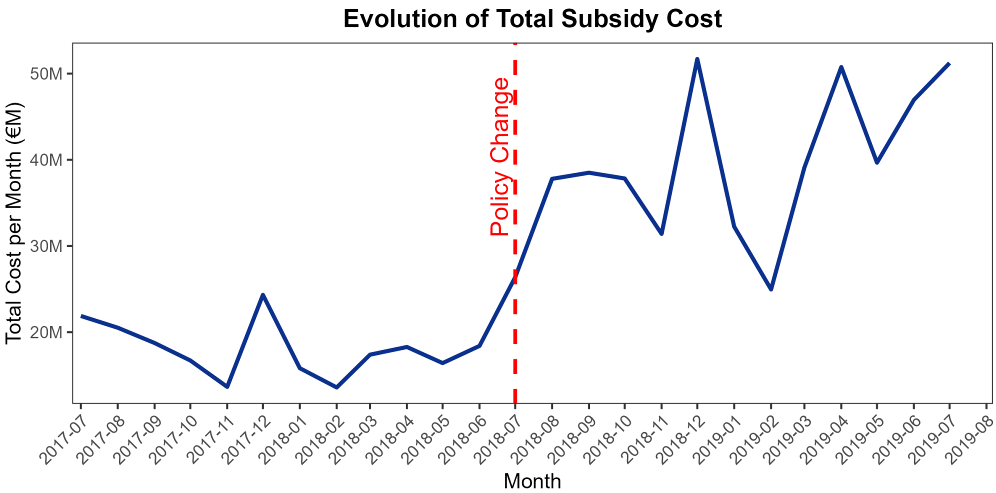

Figure 1: Evolution of program cost around 2018 increase

I next decompose this cost increase into (i) change in total demand (number of purchases), (ii) change in demand patterns (type of flights and how long in advance tickets are bought), and (iii) change in prices. For selected routes, in the one-year window around the subsidy increase (July 2017–July 2019), Figure 2 shows the change in total purchases around the subsidy change. The red bars show total purchases in each time-to-departure bin during the year immediately before the subsidy increase; the blue bars show the same for the year immediately after. The graph shows a large increase in purchases made in the last 15 days before departure. In earlier periods, purchases increased more modestly or even decreased slightly. This indicates that the increase in the subsidy rate generated a shift in purchasing patterns toward a higher share of late purchases—analogous to buying a higher-quality, higher-price version of the good.

This is complemented by the change in prices between the year immediately before the subsidy-rate increase and the year immediately after it, depicted in Figure 3. The solid line shows the evolution of median price along time to departure; I also show the 10th and 90th percentiles around the median for each period. Median prices increased for all periods. Prices in the lower tail did not change much, but the upper tail

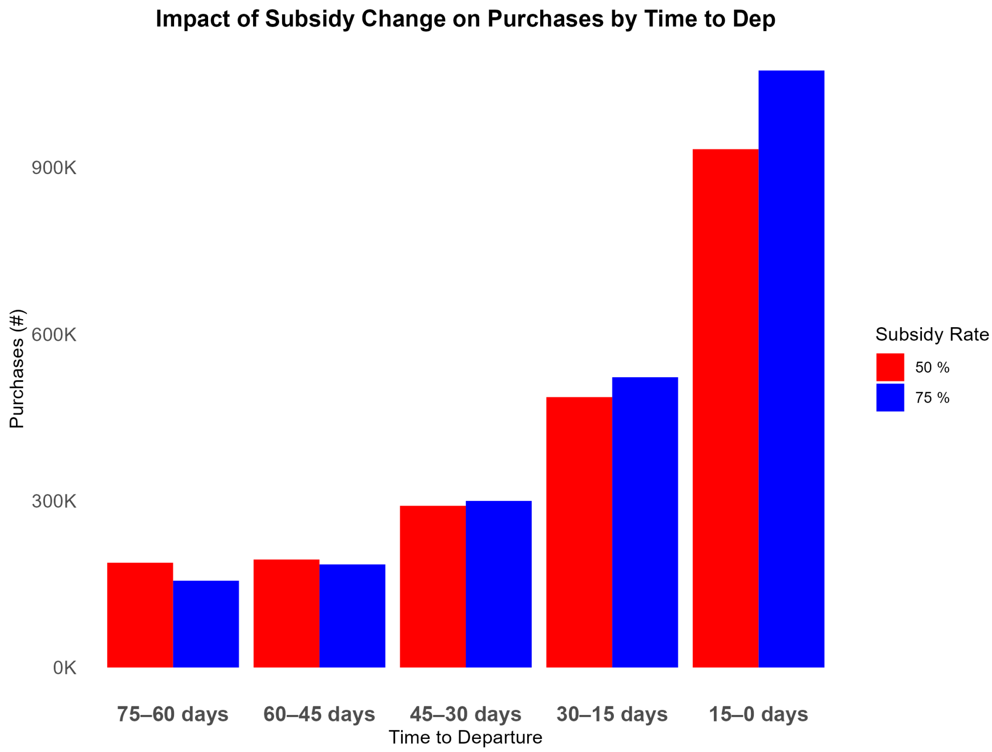

Figure 2: Change in share of purchases per period around 2018 subsidy increase

became higher, showing that very high prices became more frequent after the increase. This pattern is especially strong in the final period, which is also the period in which purchases increased most. The shape of the price path—i.e., how intertemporal price discrimination is implemented—does not appear to change significantly in the other periods. This price increase, coupled with a significant increase in quantity consumed precisely in the most expensive periods, seems to be the main driver of the increase in program cost. These initial results suggest it is worthwhile to analyze whether a change in the subsidy design can lower this cost in terms of public funds, or at least contain the sharply increasing trajectory of recent years—in other words, whether a change in design can limit firms' ability to steer consumers toward high-price products.

I also illustrate intertemporal price discrimination using Figure 4. This figure represents within-flight differences between prices in period -5 and other periods. For each flight, I choose as reference the median price in time-to-departure bin -5, and then depict for the other periods the differences in the median price within the same flight. The graph shows that the median growth of flight prices is always positive as departure approaches. While some flights see price decreases, those are the minority. By contrast, a large share of flights experience price increases as time to departure approaches, represented by the upper bar (up to the 90th percentile). This captures intertemporal price discrimination: if consumers decide to

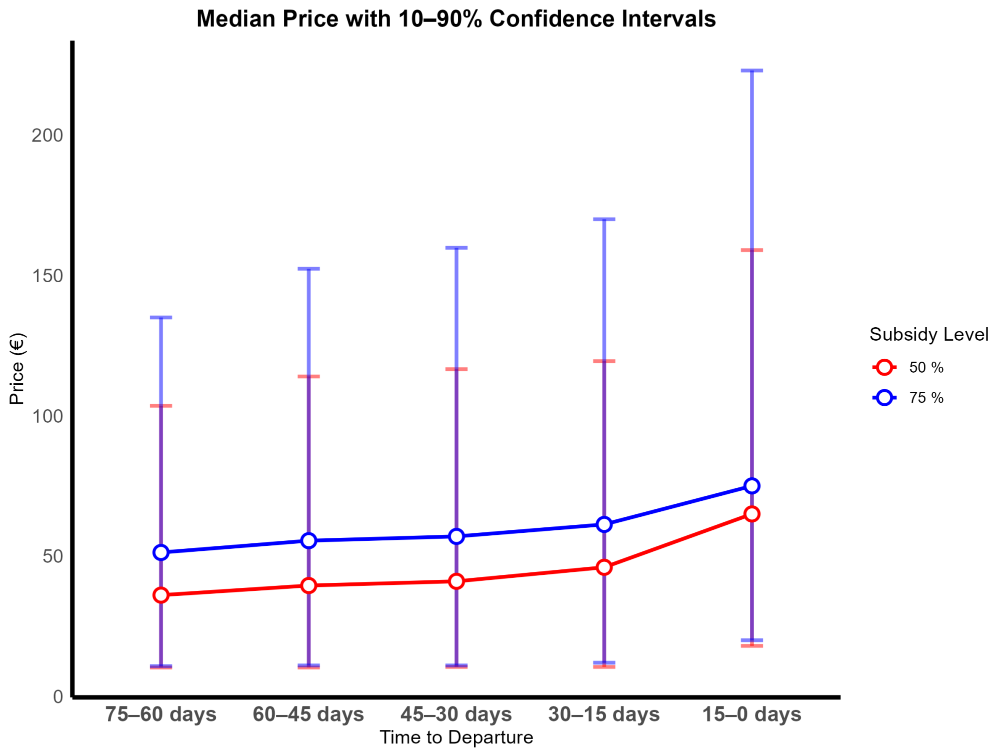

Figure 3: Prices along time to departure, before and after 2018 increase (p10–p90)

buy later, they are more likely to face higher prices, and the longer they wait, the higher the price can be relative to early purchases for the same flight.

4 Demand Model

In this section, I develop a demand model and use it for estimation of demand parameters in combination with the data introduced above. There are two groups of consumers: subsidized residents ("locals," l) and non-subsidized travelers ("tourists," t). Each consumer decides whether to buy one unit of the good or not buy at all. Consumers are forward-looking: they choose whether to buy, and also *when* to purchase. I partition the booking horizon into $T = 5$ periods, starting 75 days before departure in 15-day increments. In each period, consumers decide whether to buy one of the j available products or postpone the decision to the next period.

I define markets and products as follows. A market m is a unique combination of a *unidirectional* route, week, and year.[6] I use unidirectional routes to allow for preference differences depending on whether the trip originates in a remote territory or on mainland Spain; the former may be associated with leisure travel, whereas the latter may reflect returning home. A product j is a carrier–day-of-week–departure-time-

[6]For example, Las Palmas→Madrid in the first week of 2017 is a different market from Madrid→Las Palmas in the same week–year.

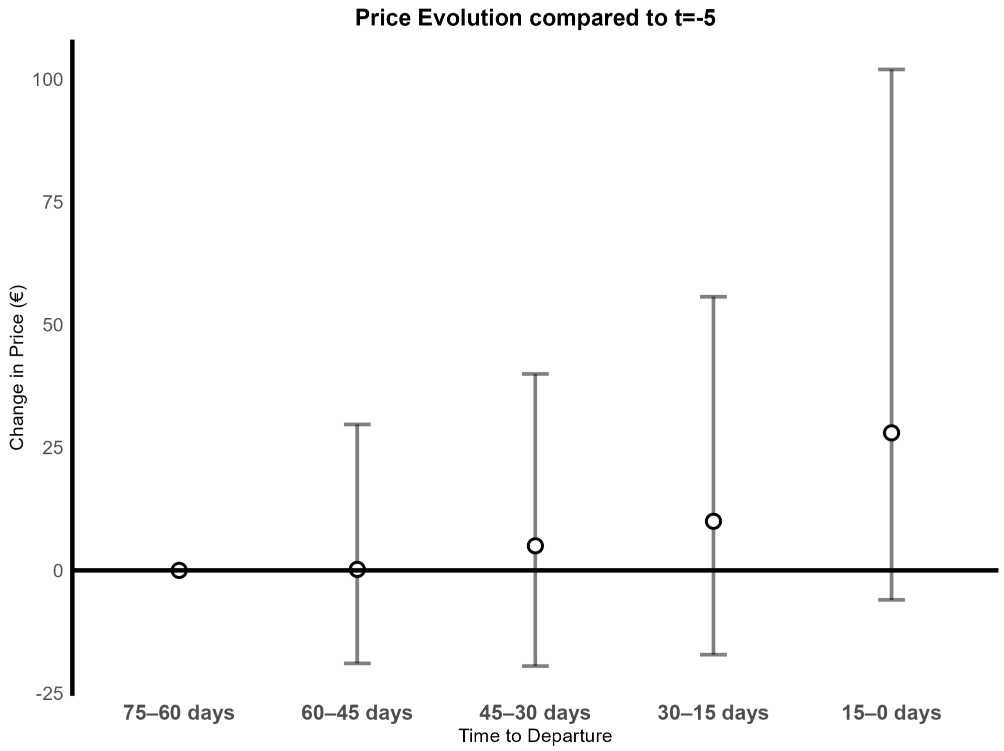

Figure 4: Change in prices from $t = -5$ for all selected flights

t	Days to departure
-5	More than 60 days
-4	45–60 days
-3	30–44 days
-2	15–29 days
-1	0–14 days

Table 1: Time-to-departure bins

	Departure hour interval
Early	Before 10 am
Mid	10 am–1 pm
Afternoon	1 pm–6 pm
Evening	6 pm–9 pm
Late	9 pm onwards

Table 2: Departure-hour bins

Table 3: Binning schemes used in the analysis.

interval combination. This choice balances computational tractability with the richness of the transaction data; while more granular (flight-level) definitions are possible, they are costly in computational terms when using the model for estimation. Thus, in each market m (route–week), a consumer chooses among the $j \in J_m \cup \{0\}$ available products or the outside option of not flying at all.

In each market $m \in \mathcal{M}$ the pool of potential consumers is given by population. Because all markets connect mainland cities with islands, the number of local consumers equals the island's population, whereas the number of tourist consumers equals the population of the relevant mainland province. Each group is partitioned into income types $h \in H = \{\text{low}, \text{medium}, \text{high}\}$. The share of each income type is taken from income-distribution data for the relevant territory, so income-group weights vary across markets m and between resident and non-resident populations.

4.1 Forward-Looking Consumers: Dynamic Discrete Choice

The goal of this subsection is to derive product-level demand by period and market. Local consumers arrive at time $-T$. In each period before the last one, $t \in \{-T, -T+1, \ldots, -2\}$ they decide whether to buy one unit of any product j or postpone the decision to $t+1$. In the last period, $t = -1$, they must either buy or exit without purchasing. Once a consumer buys product j, she exits the market. This approach differs from much of the empirical airline literature in economics and management science, which typically treats consumers as short-lived cohorts that arrive each period and do not return once they leave (e.g., Williams, 2022; Vulcano et al., 2010). I choose to allow for forward-looking behavior in consumers because I want to study how consumers re-optimize their intertemporal choice of how long in advance to buy depending on the subsidy design. The closest reference is Lazarev (2025).

If a consumer i of income h in market m buys an inside good $j \in \mathcal{J}_m$ at period $t \in \{-T, -T+1, \ldots, -1\}$ she gets the following utility:

$$u_{ijmt} = \underbrace{\delta_{jmt}}_{\text{mean utility}} + \overbrace{\alpha_i p_{jmt}(1-\tau)}^{\text{price (dis)utility}} + \underbrace{\sigma\eta_{im} + \epsilon_{ijmt}}_{\text{idiosyncratic dev.}}$$

where p_{jmt} is the posted price and τ is the ad-valorem subsidy rate.

The first term, $\delta_{j,m,t}$ represents the mean utility of buying product j in market m, t periods away from departure, common across markets and consumer types. It is important to notice that this term is allowed to vary across periods, in order to capture the fact that the mean utility of buying should be larger the closer to departure, due to the vicinity of the trip or other effects such as lower uncertainty on the desire to travel. This time-varying coefficient should pick up the disutility of paying early for a good that will only be consumed some periods from now. The subscript m captures the market-specific deviation of product j in market m. For instance, in certain markets, such as summer months, flying with a low-cost airline might have a different valuation because of higher demand and more crowded flights. The second term, $\alpha_i(1-\tau)p_{j,m,t}$, is an income-type-specific price sensitivity, which captures the fact that consumers with lower income are expected to be more price sensitive. This α_i term is decomposed as follows: $\alpha_i = \alpha + \sum_h \pi_h \mathbb{1}\{Inc_i = h\}$. The first part is a price sensitivity common across types, whereas the second part is an income-level-specific deviation from that common price sensitivity.

Finally, there are two idiosyncratic shocks for each consumer i, a shock which is constant across periods t and inside goods $j \in \mathcal{J}_m$, and a period- and product-varying one $\varepsilon_{i,j,m,t}$. The first term η_{im} introduces some taste correlation, since it is constant across periods and across all flying options. This parameter captures the fact that a consumer who has a strong taste for any flying option in a period t is more likely to have such strong taste for any flying option in any other period before departure, *vis-à-vis* the outside option of not flying in that market m. The correlation is governed by the parameter σ and the shock η_{im} is distributed normally with standard deviation equal to 1. The term ε_{ijmt} is distributed i.i.d. as EVT1.

This setting is designed to capture the trade-off between buying early at low prices versus buying late at high prices following the strategy of Lazarev (2025), who introduces consumers' uncertainty over their own future valuation of flying. If consumers buy early, they know they will pay a lower price, but they have some uncertainty over their actual desire to fly, given by β. Every period, there is a $(1-\beta)$ probability of becoming uninterested in flying. Therefore, when consumers buy early, they pay immediately a low price in exchange for some uncertain, future utility. The period-specific mean utility given by buying product j in market m, t periods away from departure, δ_{jmt}, is decomposed as follows:

$$\delta_{jmt} = \beta^{-t}\left(\delta_{AIR,j} + \delta_{DOW,j} + \delta_{H,j} + \lambda_m + \lambda_r + \lambda_m\delta_{AIR,j}\right) + \delta_{AIR,t} + \xi_{jmt}$$

The mean utility includes two effects to capture the time variation in the utility of purchasing a certain product depending on how much time there is left for departure. First, I include the uncertainty term β multiplying the time-invariant utility factors. This captures the fact that consumers will only enjoy the utility given by the specific features of the ticket jm if they are eventually interested in flying at the moment of the deadline. This parameter could also be interpreted as a discount factor, which would introduce disutility from paying early for features of the good they will only enjoy in the future. Secondly, I allow for two-way period–carrier fixed effects, to capture features such as certain airlines having worse cancellation policies (or in general any difference in utility across carriers which varies along time to departure). The presence of this term is important because I do not allow for the possibility of cancellation, so this coefficient should pick up any differences in valuations between two products due to higher flexibility in one of them. This feature is not multiplied by β, since I assume it is enjoyed instantly by consumers.

The time-invariant components of the mean utility are the following ones. I include a carrier fixed effect, a day of the week fixed effect and a fixed effect associated to the interval of the day when the flight departs. This captures the obvious fact that consumers derive different utility from flying with a flag carrier or a low-cost carrier, or between a 6 am flight and a noon flight. I also include month (m) and route (r) fixed effects, and an interaction between month and carrier, to capture the fact that the valuation of a carrier may depend on the season, because of how busy flights are. The month and route FEs also provide a heterogeneous mean valuation of flying options versus the outside option across markets. This captures the fact that in certain seasons, such as holidays, the average desire to travel is larger than in other periods. Finally, there is a three-way residual term ξ_{jmt} which captures any factor which may make utility vary across any of the three dimensions keeping the other two fixed, e.g., any factor making the utility of buying a ticket in a flight early different than buying late a ticket for the same flight, other than the discount factor.

With respect to the utility given by the outside option of not buying any product at t, its structure varies whether we are in the period right before departure $t = -1$ or any other period $t < -1$. Starting with the latter, if a consumer in period $t < -1$ decides not to purchase, i.e., to postpone the decision to the following period, she gets the following utility:

$$u_{i,0,m,t} = \beta \mathbb{E}_t \left[\max_{j \in \mathcal{J}_m \cup 0} u_{i,j,m,t+1} \right] + \varepsilon_{i,0,m,t}$$

This captures the fact that if a consumer decides to postpone her decision she will choose the option that yields the highest utility in the following period, discounted by β. If $t = -1$ there is no continuation value since it is the last period in which the good can be purchased, and hence $v_{i,0,m,-1} = \varepsilon_{i,0,m,-1}$.

Deriving consumer choice probabilities

Knowing the utility associated to each choice in each period, I will now derive the functions expressing the probability that a consumer i chooses an option j at period t. For that, I first take two simplifying assumptions which allow me to develop the utility associated with postponing the decision at every $t < -1$. I first assume consumers have perfect foresight of prices, i.e., at every period t they know the prices of all products j in all future periods. The second assumption is that consumers believe there is zero risk of being rationed if they postpone their purchase, i.e., they attach a zero probability of a flight getting full if they wait for the next period. Thanks to these two assumptions, the only uncertainty about next period's utility at the moment of deciding to postpone is given by the EVT1, i.i.d. distributed ε_{ijmt} idiosyncratic shock. Because of this distributional assumption, I can use the log-sum formula for the expectation of the maximum utility option in $t+1$ and obtain a more developed expression for the utility of postponing:

$$v_{i,0,m,t} = \beta \log \sum_{j=0}^{J_m} \exp\left\{v_{i,j,m,t+1}\right\} + \varepsilon_{i,0,m,t}$$

Using again the EVT1 distribution of the shocks, and with a bit of abuse of notation using $v_{i,j,m,t}$ to represent the utility of option j excluding the period-varying ε shock, we can write the choice probabilities for each option and consumer every period:

$$S_{i,j,m,t} = \frac{\exp\left\{v_{i,j,m,t}\right\}}{\sum_{j'=0}^{J_m} \exp\left\{v_{i,j',m,t}\right\}} = \frac{\exp\left\{v_{i,j,m,t} - v_{i,0,m,t}\right\}}{1 + \sum_{j'=1}^{J_m} \exp\left\{v_{i,j',m,t} - v_{i,0,m,t}\right\}}$$

The main complication with this expression is that the utility of the outside option $v_{i,0,m,t}$ includes recursively future expected values of postponing in all future periods. To tackle this, I follow the procedure in de Groote and Verboven (2018), which uses the conditional choice probabilities (CCPs) method developed by Hotz and Miller (1993). This method allows one to express the value of the postponing option only as a function of the utility of inside goods. The main idea behind it is that the utility of postponing the decision to tomorrow can be expressed as the utility of choosing a reference option $j = R$ the following period[7], plus a correction term which captures the fact that option R may not be the utility-maximizing option in $t+1$:

$$\begin{aligned} v_{i,0,m,t} &= \beta \log \sum_{j=0}^{J_m} \exp\left\{v_{i,j,m,t+1}\right\} \pm \beta \log\left(\exp\left\{v_{i,R,m,t+1}\right\}\right) = \\ &= \beta v_{i,R,m,t+1} - \left(\beta \log\left(\exp\left\{v_{i,R,m,t+1}\right\}\right) - \beta \log \sum_{j=0}^{J_m} \exp\left\{v_{i,j,m,t+1}\right\}\right) = \beta v_{i,R,m,t+1} - \beta \log\left(S_{i,R,m,t+1}\right) \end{aligned}$$

[7]The product chosen as reference product does not really matter, as long as it is consistently chosen as reference product all periods.

This technique allows me to get rid of the values of postponing. Thanks to this, I can derive choice probabilities only as a function of inside-good characteristics. The function $S_{i,j,m,t}$ below represents the probability that a consumer i chooses to buy product j in market m and t periods before departure:

$$S_{i,j,m,t} = \frac{\exp\{\tilde{v}_{i,j,m,t}\}}{1+\sum_{j'=1}^{J_m}\exp\{\tilde{v}_{i,j',m,t}\}} \qquad \text{where } \tilde{v}_{i,j,m,t} = \begin{cases} v_{i,j,m,t} - \beta v_{i,R,m,t+1} + \beta\log\left(S_{i,R,m,t+1}\right) & \text{if } t < -1, \\ v_{i,j,m,t} & \text{if } t = -1. \end{cases}$$

It is worthwhile to analyze in more detail the components of the term $\tilde{v}_{i,j,m,t}$ for $t < -1$. Notice that this term is interpreted as the difference in utility between any inside good and postponing to tomorrow, and that the latter is expressed as choosing option 1 tomorrow, plus a correction term in case option 1 is not the preferred one in $t+1$. It can be decomposed into the different parts of utility as follows:

$$\tilde{v}_{i,j,m,t} = \underbrace{\delta_{j,m,t} - \beta\delta_{R,m,t+1}}_{\tilde{\delta}_{j,m,t}} + \alpha_i(1-\tau)(\underbrace{p_{j,m,t} - \beta p_{R,m,t+1}}_{\tilde{p}_{j,m,t}}) + (1-\beta)\sigma\eta_{im} + \beta\log\left(S_{i,R,m,t+1}\right)$$

This expression shows how for forward-looking consumers, the relevant variables when deciding whether to buy early or wait for the final period are how much the price will change if they wait for next period, as well as how much will time-relevant characteristics (i.e., the interaction between carrier and time to departure) change. In all periods before $t = -1$, the time-to-departure-invariant fixed effects, such as carrier or day-of-the-week fixed effects, disappear. These elements of the utility function are only relevant for the decision of consumers still present in the final period $t = -1$, who have to decide between buying a product or not consuming at all.

From choice probabilities to demand functions

The choice probabilities derived with the above formula are in reality the choice probabilities *conditional* on the consumer still being present in the market in period t, that is, not having bought the good previously, since for the moment purchasing is the only source of attrition in the model. In the first period $t = -T$ the conditional and unconditional purchase probabilities coincide, but for the subsequent periods the unconditional ones are equal to the product between the conditional ones, times the probability of still being present in the market. The latter is also a product between the probability of staying in the market after $t-1$, conditional on having stayed until then, times the probability of having stayed, i.e., not having purchased before $t-1$. Let us define $\mathbb{N}_{i,m,t}$ as the unconditional probability of a consumer i of not having bought any product before period t, whereas $\mathbb{N}_{i,m,t|t-1}$ represents the same probability, conditional on not having bought before $t-1$. We can define the former object as the following product

$$\Pr(\text{Cons } i \text{ present at } t) \equiv \mathbb{N}_{i,m,t} = \mathbb{N}_{i,m,t|t-1}\mathbb{N}_{i,m,t-1} = \left(1 - \sum_{j=1}^{J_m} S_{i,j,m,t-1}\right)\mathbb{N}_{i,m,t-1} = \prod_{s=-T}^{t-1}\left(1 - \sum_{j=1}^{J_m} S_{i,j,m,s}\right)$$

Therefore, we can conclude this consumer decision model section with the desired output, the choice probabilities for all options $j \in \mathcal{J}_m$, for all markets $m \in \mathcal{M}$, for all consumer types $h \in \mathcal{H}$ and for all periods $t \in \{-T, -T+1, \ldots, -1\}$, which are equal to the following product, represented as a function of parameters of the utility function $(\boldsymbol{\delta}, \boldsymbol{\pi}, \alpha, \sigma, \beta)$:

$$\Pr(\text{Cons } i \text{ buys } j \text{ at } t) \equiv \mathbb{P}_{i,j,m,t}((\boldsymbol{\delta}, \boldsymbol{\pi}, \alpha, \sigma, \beta)) = \mathbb{N}_{i,m,t}(\boldsymbol{\delta}, \boldsymbol{\pi}, \alpha, \sigma, \beta) \times S_{i,j,m,t}(\boldsymbol{\delta}, \boldsymbol{\pi}, \alpha, \sigma, \beta)$$

We can develop this further by integrating over unobserved types i within income level h, in order to obtain the probability that a consumer of income type h purchases product j in market m at period t. It is important to recall here that the distribution of unobserved types i is independent of income type h:

$$\Pr(\text{Cons of type } h \text{ buys } j \text{ at } t) \equiv \mathbb{P}_{h,j,m,t}((\boldsymbol{\delta}, \boldsymbol{\pi}, \alpha, \sigma, \beta)) = \int_i \mathbb{N}_{i,m,t}(\boldsymbol{\delta}, \boldsymbol{\pi}, \alpha, \sigma, \beta) \times S_{i,j,m,t}(\boldsymbol{\delta}, \boldsymbol{\pi}, \alpha, \sigma, \beta) dF(i)$$

The model developed in this section allows me to derive the demand function of local consumers in market m, for each product j and period t. To obtain local consumers' demand I just need to sum across income groups. The demand of each income group h is equal to the purchase probability of a consumer of income h, times the number of consumers of income h in that market, i.e., $D_{h,j,m,t} = N_{h,m,t}\mathbb{P}_{h,j,m,t}$. Total local demand is the sum across income levels.

$$D^l_{j,m,t} = \sum_h D_{h,j,m,t}$$

4.2 Demand functions of tourists

For tourists, per-period demand has the same functional form as for locals, but I allow for different coefficients, e.g., their price sensitivity α^t is different from the α of local consumers. This is meant to capture the fact that tourists may have a different price sensitivity due to different travel habits than locals, mostly driven by the fact that tourists are generally traveling for leisure, while locals may often travel due to work-related reasons or other reasons different than leisure. I also allow for the product mean utilities δ_{jmt} to be different for tourists, to capture the fact that the relative utility of tourists of buying a product versus not buying at all is different. For instance, one can think that the outside option for tourists should be more attractive than for locals, because the former group may be more willing to substitute for another market (e.g., traveling for vacation to another island or during another week) than locals, who cannot really substitute traveling home for traveling to another destination. Furthermore, tourists do not receive any price discount, and therefore $\tau = 0$ for this group of consumers. Other than that, the demand function of tourists is derived following the same procedure as for locals. Therefore:

$$D^t_{h,j,m,t}(\boldsymbol{\delta}^t, \boldsymbol{\pi}^t, \alpha^t, \sigma^t, \beta) = N^t_{h,m,t}\mathbb{P}_{h,j,m,t}$$

5 Estimation

The aim of this section is to obtain consistent estimates of the parameters driving consumers' decisions according to the choice probabilities functions developed in the previous section. That is, I aim to estimate $\Theta = (\boldsymbol{\delta}, \boldsymbol{\pi}, \alpha, \sigma, \beta)$ for both groups, locals and tourists. The estimation of the parameters for both of these groups is conducted separately. This is because of the difference in the data available for each group; whereas for the local, subsidized consumers I observe how long in advance each purchase was made, for tourist, non-subsidized consumers I only observe the total amount of consumers of this type by flight, but I do not observe any information about when those purchases happened. Therefore, for the tourist group I can only estimate the parameters which are not related to time to departure. I am forced to assume the parameters governing intertemporal preferences on how long in advance to buy are equal to those of locals. While this is not ideal, I believe it is not a major hindrance for the project, due to the fact that to answer my question I am interested in the intertemporal substitution of the local consumers who are entitled to the subsidy, but not necessarily in that of the tourists. I will first explain in detail the estimation of demand parameters for local consumers, and I will afterwards do a shorter explanation of how tourist parameters are estimated.

For the remainder of the paper, I use a subsample corresponding to the selected routes defined above, during the year 2017. This is done for computational purposes. Using all observations becomes costly in computational terms due to the large size of the data. Estimated parameters are not very sensitive to changing the subset of routes and periods used for the analysis. This also allows for a cleaner identification of the price parameter, thanks to using a unique subsidy rate for all observed purchases, since the subsidy rate increase happened in summer 2018 and is thus left out of the estimation sample. These routes are the most representative for my analysis, since they are the markets with a bigger number of consumers and more airlines present.

5.1 Estimating the Demand of Local Consumers

The estimation algorithm for local consumers consists in a dynamic discrete choice estimation, with an additional challenge caused by the presence of zero purchase observations, i.e., for some product j, market m and time to departure t combinations there are no consumers buying, so $q_{jmt} = 0$. An example of this would be that in a Wednesday morning flight in a small route in the middle of February, no consumer is buying a ticket in the time-to-departure bin between 75 and 60 days. The presence of observations with zero purchases is a problem for applying the conventional demand estimation machinery developed since Berry, Levinsohn and Pakes, 1994 (hereinafter BLP), because this methodology necessarily relies on all products having a strictly positive market share. To circumvent this problem, I do the estimation of locals' demand function parameters in two stages. In the first stage, I estimate a selection model which explains why some products have zero purchases in certain periods. In the second stage, I conduct a BLP estimation assuming that only products with strictly positive markets shares enter the consideration sets of consumers, following the procedure of Dubé et al. (2020). To deal with the potential selection bias that this can introduce in the estimation, I explicitly control for the unobservable characteristics driving selection of products into the strictly positive purchase group.

5.1.1 Selection Stage

Following Dubé et al. (2020), I assume that products with zero market shares in a certain market and period do not enter the alternative sets of consumers in that specific decision stage. Simply dropping those products without any adjustment would cause selection bias in the demand estimates, because products with strictly positive purchases are more likely to yield high unobserved utility to consumers. Hence, $\mathbb{E}[\xi|q_{jmt} > 0] > 0$, which breaks the necessary assumption for identification of demand parameters. To deal with this, I decompose the unobservable ξ as follows: $\xi_{jmt} = \mu_{jmt} + \nu_{jmt}$. I assume $\mathbb{E}[\mu|q_{jmt} > 0] = 0$, i.e., μ represents the unobserved quality part uncorrelated with selection probabilities, and ν represents the problematic part which is correlated with the selection process.

To obtain an estimate of ν, $\hat{\nu}$, which can be included in the random-coefficients logit estimation, I set up a selection model, which includes the following variables determining whether a product has zero purchases in a specific market period ($\{d_{jmt} = 0\}$). First, a fifth-degree polynomial of time to departure (period). Second, a group of variables summarizing the intensity of competition in that market ($\mathbf{w}$), which includes the number of competing flights and the total number of offered seats in that market, in that route and date, in that route and date by that airline, and in that route, date and time interval. The idea here is that the more crowded a product space is, the more likely one of the products gets zero sales in a specific period. Finally, I also include airline, day-of-the-week, hour-interval and market (route-week) FEs in $\mathbf{x}$. Finally, the unobservable ν_{jmt} captures all other factors which make a product not considered in a specific time-to-departure–market pair.

$$\{d_{jmt} = 1\} = \sum_{s=1}^{5} \gamma_s(-t)^s + \mathbf{w}'\omega_{\mathbf{1}} + \mathbf{x}'\omega_{\mathbf{2}} + \nu_{jmt}$$

I estimate this model using a linear probability model and OLS. This means I do not assume any specific distribution for the selection error ν. I recover the residuals $\hat{\nu}_{jmt}$, which will be used in the second stage of the estimation process. Those residuals are the conditional mean of the selection error, conditional on the value of the selection observables. Only the residuals of observations with $q_{jmt} > 0$ will be used, and therefore residuals are equal to $\mathbb{E}[\nu|d_{jmt} = 1]$. This is equivalent to a Heckman two-step selection procedure, with semiparametric selection and utility errors, as presented in Cameron and Trivedi (2005). The selection variables $\boldsymbol{w}$ and the time-to-departure polynomial are the necessary variables not entering the utility function which provide identification of the utility parameters using the selected sample. One can think of them as selection instruments which correct the endogeneity between price and the selection unobservable shock.

5.1.2 Random Coefficient Logit demand estimation

Using the subsample of product–market–period with strictly positive purchases ($q_{jmt} > 0$), I use the predicted choice probabilities developed in Section 3 to set up a BLP-style random-coefficient logit estimation. Recall that the probability of a consumer i of income h buying good j in market m t periods away from departure is given by $\mathbb{P}^i_{h,j,m,t}$. To aggregate across unobserved types i, I draw 200 observations from a Halton sequence and I compute the average probability of purchase across the 200 draws. This yields a probability of purchase at income–product–market–time-to-departure level: $\mathbb{P}_{h,j,m,t} = (1/200)\sum_{i=1}^{200} \mathbb{P}^i_{h,j,m,t}$. For the contraction mapping between observed and predicted shares, I also aggregate shares across income groups using the observed weight of each income group, obtained from population data: $\mathbb{P}_{jmt} = \sum_h \omega^h \mathbb{P}_{h,j,m,t}$.

As it is usually done in the random-coefficients BLP procedure, like in Train (2007) or Berry et al. (2004), I divide the parameters into those that enter the estimation linearly and non-linearly. The first group contains the fixed effects in the utility function (the components of $\boldsymbol{\delta}$), as well as the common price sensitivity α. For simplifying notation, from now on the common price sensitivity is included in the mean utility terms $\boldsymbol{\delta}$. The second group contains $(\sigma, \beta, \boldsymbol{\pi}, \boldsymbol{\delta})$. Following the usual BLP procedure, the first three groups of non-linear parameters, $(\sigma, \beta, \boldsymbol{\pi})$, which I label as θ_2, fully determine the product mean utilities $\boldsymbol{\delta}$. Thanks to having only products with $q_{jmt} > 0$, I can employ the usual contraction mapping developed in the seminal BLP paper to obtain the $\boldsymbol{\delta}$ associated to each θ_2, which gives me a mapping $\boldsymbol{\delta}(\theta_2)$. This allows me to reduce dramatically the number of parameters to be estimated.

I start the estimation routine with a guess of the non-linear parameters, $\boldsymbol{\delta}(\theta_2)$. For any guess of θ_2, there is a unique vector of $\boldsymbol{\delta}$, which solves the contraction between observed and predicted market shares. This technique is the standard one first introduced by the BLP seminal paper. The only relevant difference to be noted here is that the usual contraction algorithm must be done using the conditional shares in each period, i.e., using the shares of each product among consumers still present in the market. Also, the $\boldsymbol{\delta}$ terms should be the $\tilde{\boldsymbol{\delta}}$ terms which contain the correction for the outside option, as explained in Section 3. If one uses the unconditional shares, the contraction fails because the δ_{jmt} of products in the initial periods impact the unconditional shares of products in the final periods. Therefore, the usual updating rule of the BLP contraction $\boldsymbol{\delta}' = \boldsymbol{\delta} + \log(S^{obs}) - \log(\mathbb{P}(\boldsymbol{\delta}, \theta_2))$ does not guarantee that this is indeed a contraction unless we use $\tilde{\boldsymbol{\delta}}$ and the period-conditional shares $S_{h,j,m,t}$.

Once I obtain the estimates of the non-linear parameters $\hat{\theta}_2$ and its associated $\tilde{\boldsymbol{\delta}}(\hat{\theta}_2)$, I first back out $\boldsymbol{\delta}$ using the fact that $\tilde{\boldsymbol{\delta}}_t = \boldsymbol{\delta}_t - \beta\delta_{R,m,t+1}$ and that at $t = -1$, $\tilde{\boldsymbol{\delta}}_{-1} = \boldsymbol{\delta}_{-1}$. I then decompose these $\boldsymbol{\delta}$ into the mean utility components explained in Section 3.1, the common price sensitivity term and an unobservable term at product, market, period level ξ_{jmt}, which is decomposed into the selection unobservable ν_{jmt} and μ_{jmt}. As it is standard in the Empirical IO literature, I assume μ_{jmt} is orthogonal to non-price characteristics of the products $\boldsymbol{X}$, which is required for identification, i.e., $\mathbb{E}[\mu\boldsymbol{X}] = 0$. A justification for this assumption is that non-price characteristics are difficult and take some time to modify, and therefore they should not be affected by specific demand shocks to a product. I include the residuals $\hat{\nu}_{jmt}$ from Stage 1, to control for the unobservables driving selection:

$$\delta_{jmt} = \beta^{-t} \left(\delta_{AIR,j} + \lambda_m + \lambda_r + \lambda_m\delta_{AIR,j}\right) + \delta_{AIR,t} + \alpha p_{jmt} + \psi\hat{\nu}_{jmt} + \mu_{jmt}$$

The parameters in this equation can be estimated using OLS. However, as it is usually the case, there are endogeneity concerns in this specification regarding price p_{jmt}, since I assume that it is not necessarily the case that $\mathbb{E}[\mu\boldsymbol{p}] = 0$. The advantage of this estimation approach which separates non-linear and linear parameters is that endogeneity only affects the linear parameters and therefore can be dealt with using 2SLS, as I explain in the coming section.

5.1.3 Dealing with Endogeneity

The main issue with the specification developed in the previous section is the potential endogeneity of prices. Recall that in my current empirical design, observations are defined at *market–product–period-to-departure–income group* level, i.e., $p_{j,m,t}$ and $\mu_{j,m,t}$, and that product is equivalent to carrier–day of the week–hour of departure. If we think about the components of mean utility which are not controlled for directly in the specification above, it is likely that some of them are correlated with prices. For instance, take the three-way FEs in the mean utility, i.e., factors affecting differentially the same product, in the same market, but in different periods, other than the discount factor. The current specification cannot include this as a control due to not having enough degrees of freedom (it would be an observation-specific fixed effect). Moreover, it could potentially be the case that there exists some shock to demand for product j, market m along time to departure, e.g., a local team from Tenerife qualifying for the next round of the Spanish national football cup in Barcelona. This type of factor would not be controlled for in my specification, and would affect prices. Despite these types of events being rare, it makes it worthwhile to instrument prices in this specification.

I am using four sets of instrumental variables to deal with this endogeneity. Three of them are usual instruments in Empirical IO:

1. A BLP-style instrument which is the proportion of flights by each competing airline in market m. This is the equivalent of the average of rival product characteristics in the current setting.
2. The number of competing products (i.e., number of competing airlines) and the number of competing flights (i.e., sum of flights of competing airlines).
3. A Hausman–Nevo set of instruments which consists of the average price of the same airline in (i) similar routes in the same month, and (ii) a selection of other months in the same route.

To these traditional instruments, I add some instrumental variables specific to the airline industry. Firstly, I use the average initial capacity of aircraft for each airline (Williams, 2022; Lazarev, 2025; Berry and Jia, 2010). This is not directly a price determinant for every period t, but spare capacity in period t is actually an important determinant of airline price decisions. Since the latter is both unobserved and endogenous, I use initial capacity as a proxy which can be considered as exogenous, at least in the short term, due to the significant costs of reallocating the airline fleet across routes. I also add the count of flights and sum of seats across flights used as selection instruments in Section 1. Finally, I also include as an instrument whether a flight has as origin or destination a hub airport for the carrier. This is a proxy of a flight ending in a hub, which makes marginal costs smaller, as in Berry and Jia (2010).

The validity of these instruments is justified as follows. First of all, they are relevant according to the pricing model I develop in Section 5. Rival products' characteristics enter the optimality conditions of firms because of the functional form of logit demand functions. The number of competing products also has a relevant impact in logit demand function settings, since it determines the number of terms in the denominator of the choice probability function. Hausman–Nevo instruments are used as a proxy of cost shocks which are common across different routes. If the price in another route increases due to an increase in fuel price, this should also be reflected in the price of the route. Hub indicators also affect the marginal cost of providing the service, since flights departing from hub airports are less costly for carriers, according to Berry and Jia (2010). Finally, capacity constraints directly impact pricing decisions.

It can also be argued that these instruments satisfy the exclusion restriction. The assumption that non-price characteristics $\boldsymbol{X}$ are uncorrelated with the unobservable μ also implies that rival product characteristics $\boldsymbol{X}_{-j}$ are uncorrelated with product j's demand shock μ_j. A similar logic applies to the number of competing products; I assume that changing the number of products is a costly decision in terms of time and money which does not depend (at least in the short term) on demand shocks to a specific flight. The argument for the exclusion of the hub airport indicator is similar; deciding which airport is the hub of a carrier is a quite costly procedure that cannot be changed quickly. With respect to the Hausman–Nevo instruments, the assumption needed for their exclusion is that common cost shocks across markets driving price variation are uncorrelated with demand shocks affecting specific products in market m. Finally, with respect to capacity constraints, the strongest argument supporting exclusion is again the fact that altering the capacity offered (the total number of seats offered on a certain day, hour by a certain airline in a certain route-week) is a costly decision which should not change (at least in the short term) due to demand shocks to specific flights. This is supported by the slot allocation systems of European airports, which are quite inflexible and make it very difficult to obtain an extra slot to offer an additional flight in the short term (Marra, 2025).

5.2 Estimation of Non-Subsidized Consumers Demand

To obtain total quantity sold to non-subsidized (tourists) consumers per flight, I use the information on total passengers per flight, which I obtain from the AENA dataset. I then subtract the observed purchases by local consumers and I obtain the number of tourists per flight. I then aggregate using the same product market definition as for tourists, i.e., carrier–hour interval–day of the week, and week–unidirectional route. As measure of price paid by tourists in a product–market I use median price for that product–market, from the dataset on all subsidized purchases. Importantly, quantity consumed by tourists is not disaggregated by time-to-departure period within product, and therefore I am constrained to do a static demand estimation for this group of consumers. Since I do not observe purchases disaggregated by time-to-departure period, there is no issue with zero purchases in certain periods for non-subsidized demand. Using this information, plus product and market characteristics, I conduct a random-coefficient logit, static discrete choice estimation, with a continuum of unobserved types on their taste for flying, with exactly the same structure as subsidized consumers. I now show the utility and the predicted share of product j in market m for a consumer with unobserved type i with income level h:

$$u_{ihjm} = \delta_{jm} + \alpha_h p_{jm} + \sigma\eta_{im} + \epsilon_{ijm}$$
$$\mathbb{P}_{ihjm} = \frac{\exp\{\delta_{jm}+\alpha_h p_{jm}+\sigma\eta_{im}\}}{1+\sum_{j'}\exp\{\delta_{j'm}+\alpha_h p_{j'm}+\sigma\eta_{im}\}}$$

Using the observed weights of each income group in the population, I set up a standard BLP contraction to obtain the mean utilities δ associated with each guess of non-linear parameters. Then, I decompose δ_{jm}, getting rid of the period terms, due to the lack of period-specific purchase data for this group of consumers. Finally, I set up a moment function using the residuals ξ from this linear regression and the instruments, which are the same as for subsidized demand, except the time-to-departure ones. The estimated parameters are presented in the table below.

In order to include this group of consumers in the counterfactual experiments, I take these estimates and then I impute the intertemporal parameters from the subsidized consumers' demand estimation, i.e., the discount factor β and the two-way FE for airline and time to departure. Due to the lack of information on the timing of purchases by non-subsidized consumers, I am forced to make the assumption that intertemporal tastes are equal for subsidized (local) and non-subsidized consumers (tourists). Importantly, non-subsidized consumers will have a price sensitivity parameter α^t different from the one for subsidized consumers, due to the different characteristics of both consumer types, both in terms of traveling motives and in terms of income distributions in the islands and in Mainland Spain provinces. Their valuation of flying options, given by $\boldsymbol{\delta}$, is also different than that of locals. Therefore, I allow for different relative valuation of the outside option *vis-à-vis* the flying options between locals and tourists, which will impact the price elasticities of both groups.

5.3 Results

The table below shows the preliminary results using this estimation procedure. In these initial results, I

	Parameter	Locals	Tourists
β	Discount factor	0.9	-
σ	Taste correlation	0.0158	0.0275*
α	Price sensitivity	-0.0797***	-0.1375***
π_l	Deviation low income	-0.0183***	-0.0016**
π_l	Deviation high income	0.0429***	0.1201***

take the discount factor β from the results in Lazarev (2025), who obtains a discount factor of around 0.9 using a very similar demand setting to mine. The non-linear parameters θ_2 have the following results. The taste correlation σ is close to 0. With regards to the income-specific deviations from the price sensitivity, the estimated effects are as expected, and both low- and mid-income levels are significantly more price sensitive than high-income consumers. It is also important to note how tourists have a larger price sensitivity in absolute value than local consumers.

With respect to the other parameters, I will present some selected results on the multiple fixed effects present in my demand specification. For locals, the FE of traveling with Ryanair is equal to -11.12, whereas that of traveling with Iberia, the Spanish flag carrier is equal to -6.19. Using the logit coefficients interpretation from Train (2009), this means that a local consumer of low income buying last minute is willing to pay $-\frac{-6.19-(-11.12)}{0.0797+0.0183} = 50.30$€ for switching from Ryanair to Iberia in the baseline month (August). A high income consumer, by contrast, due to her lower price sensitivity, is willing to pay $\frac{-6.19-(-11.12)}{0.0797-0.0429} = 133.97$€. With respect to the day of the week and time to departure preferences, the day that yields the largest utility is Saturday. Using the same formula, a low income consumer would be willing to pay 12.25€ for traveling Saturday instead of Monday, which is the day with lowest utility. The most attractive interval of the day to travel is the Early one (before 10 am). Low income consumers are willing to pay 12.35€ for departure in the early interval compared to the Afternoon interval (1pm-6pm). If we do the same analysis for tourists,

To further present the results, I also show some selected facts about elasticities, which are computed with the usual formula $\epsilon_{jk} = (\partial D_j/\partial p_k) \cdot (p_k/D_j)$. ϵ_{jj} represents own-price elasticities. The average own-price elasticity for local consumers is -3.74. The same figure for tourists is -4.10. Tourists are more price elastic than locals, although the difference is not very large. Looking at how price elasticity varies across time to departure, for both groups, in Figure 5, in general demand becomes more inelastic as departure approaches, except for local consumers in the final period, who become more elastic. These elasticities are in line with what is found by Lazarev (2025), the most comparable reference in terms of demand model and industry.

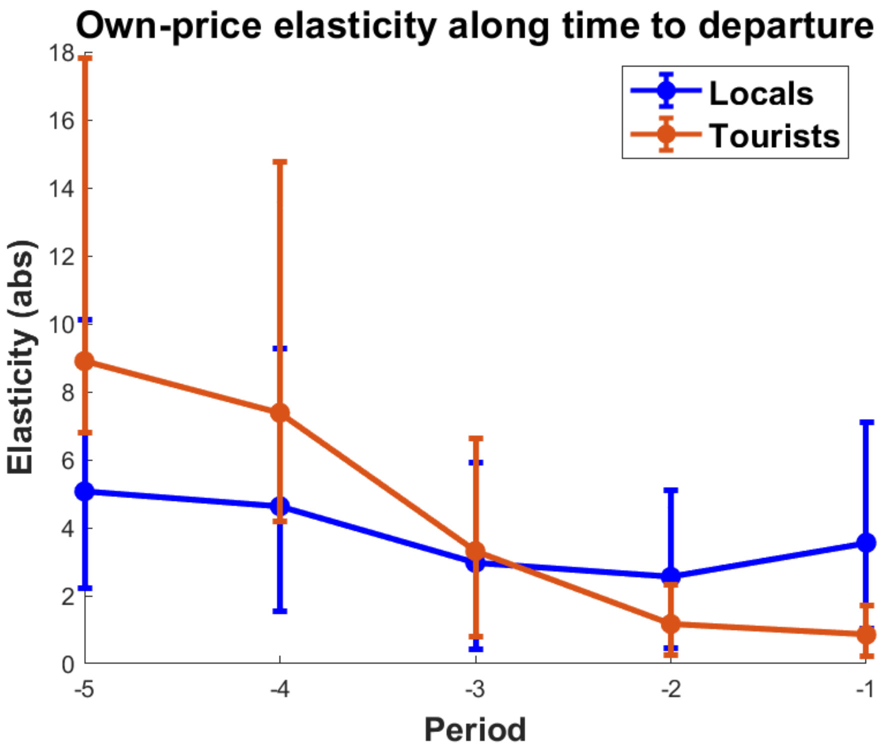

Figure 5: Evolution of own-price elasticities for locals and tourists along time to departure

6 Supply Side: A Model of Oligopoly Intertemporal Competition

In the supply side there are $\mathcal{F}_m$ multiproduct firms in each market m, which compete in the $T = 5$ periods selling their products $j \in \mathcal{J}_{fm}$. Each market is modelled separately, so I abstain from spillovers across markets. Firms can sell K_{jm} units of each of their products, given by the total number of seats they offer for each product j in market m (i.e., in a certain route–week). Firms can sell these units over the $t \in \mathcal{T}$ periods, and they can do intertemporal discrimination, i.e., they can choose a different p_{jmt} for each period t. Firms choose the price path $\boldsymbol{p}_{j,m}$ to maximize the profit in market m, competing according to a Nash–Bertrand competition structure. For the moment, I only allow firms to choose their intertemporal path of prices for all $t \in T$ periods before departure, but I do not allow them to choose other variables such as the capacity of aircraft, the number of flights they offer per route or the routes they want to serve. While these are all interesting angles to study, I leave them for future versions of the project.

The profit function of firms per product j in a given market m looks as follows:

$$\Pi_{jm} = \sum_{t=-T}^{-1} (p_{jmt} - mc_{jmt}) \left(D_t^s(p_{jmt}, p_{j'mt}; \tau) + D_t^t(p_{jmt}, p_{j'mt}) \right)$$

The demand functions are taken from the consumer decision model developed in Section 3. I now proceed to deriving the optimality conditions that firms use to choose the price schedule for all their products. Using these conditions, I can also back out the marginal costs for each product j.

6.1 Deriving the equilibrium of the intertemporal pricing game

In this first attempt, I make two assumptions about the intertemporal pricing competition game among airlines which allow me to derive a unique price equilibrium. First of all, I assume that capacity constraints are never binding in any market, i.e., there is always space in some flight within a product (airline–day of the week–interval of the day) in a market (route–week combination). There seems to be anecdotal evidence supporting this assumption. Secondly, I assume prices are chosen with commitment in the initial period, i.e., airlines choose a price path for their product before consumers can start buying, and they stick to such prices. One can think of this as airlines committing in advance to a certain price for purchases made 40–50 days before departure, another price for purchases made 30–40 days before departure, and so on and so forth until the last 10 days before departure. These assumptions allow me to derive a unique Nash–Bertrand equilibrium of the intertemporal pricing game. Such equilibrium is characterized by the First Order Conditions (FOCs) of the intertemporal pricing problem of the firms:

$$\begin{aligned} p_{jmt} \ : \ & \underbrace{D_t^s + D_t^t + (p_{jmt} - mc_{jmt})(\partial D_t^s / \partial p_{jmt} + \partial D_t^t / \partial p_{jmt})}_{\text{effect on } t} + \\ & + \underbrace{\sum_{t' \neq t} D_{t'}^s + D_{t'}^t + (p_{jmt'} - mc_{jmt'})(\partial D_{t'}^s / \partial p_{jmt'} + \partial D_{t'}^t / \partial p_{jmt'})}_{\text{effect on other periods}} = 0 \end{aligned}$$

It is worthwhile to write a note on the effect of price decisions on other periods. With respect to past periods, a higher price in period t makes demand higher in previous periods. Since I assume consumers perfectly predict future prices, a higher future price will make fewer consumers delay their purchase, all else equal. With respect to future periods, a higher price in period t will increase demand in future periods, since more consumers will decide to postpone their purchase and there will be a larger mass of consumers left in the market in the final periods.

The unique Nash–Bertrand equilibrium is defined as the vector of prices $\mathbf{p}^*$ which simultaneously solve all FOCs for all products j, in all markets m and for all periods t.

6.2 Obtaining estimates of the marginal costs

With the unique equilibrium defined as stated above, I can use the observed prices in the data and the estimated demand parameters from Section 5 to obtain estimates for marginal costs for every product j, in market m and period t. There is a unique vector of marginal costs, $\mathbf{c}^*$ that satisfies the FOCs and which are compatible with the observed equilibrium prices given the estimated parameters. That vector $\hat{\mathbf{c}}$ is the vector of marginal cost estimates. In particular, taking the FOC expression from above, we can solve for implied marginal costs as follows, where p_{jmt} is the observed price in data and the mark-up expression is computed using observed prices and product characteristics and estimated demand parameters:

$$\hat{c}_{jmt} = p_{jmt} + \sum_t D_{jmt}(\mathbf{p}) \frac{\partial D_{jmt}(\mathbf{p})}{\partial p_{jmt}}$$

Figure 6 below shows the estimates of marginal costs:

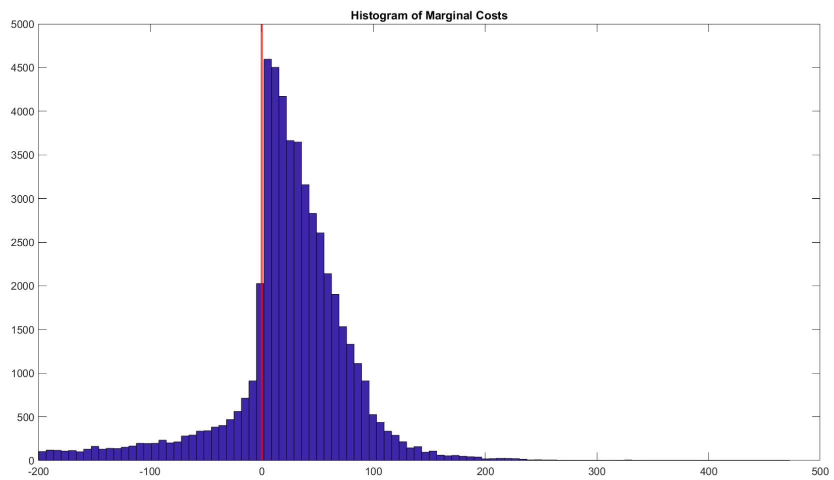

Figure 6: Distribution of marginal costs

There are a percentage of marginal cost observations which are negative. However, this is only 18.3% of the observations. A way to interpret marginal costs varying over time for the same flight is the one used in Williams (2022) and Betancourt et al. (2024): the marginal cost of selling a ticket is the opportunity cost of selling it today and not being able to sell it in future periods, when airlines are facing potentially a more inelastic demand. Therefore, marginal costs should vary along time to departure for the same product.

7 Counterfactual Experiment: Changing the Subsidy Design

With the demand parameters and the marginal cost estimates in hand, I now run the counterfactual experiment of changing the subsidy design from the current *ad valorem* to a unit design. After doing so, and changing appropriately the subsidized consumers' demand function, I recompute the price equilibrium in each market using that new demand function. To recompute this equilibrium, I calibrate the amount of the unit subsidy as the amount that makes total demand in every market (across different products and periods) remain at the observed level. That is, total consumption per market must stay constant, but the composition of such consumption can change, so the shares of the different inside goods are allowed to change[8]. The fixed subsidy which more closely generates the observed levels of consumption in all markets is 32.46€. This is computed as the fixed subsidy which generates a demand aggregated across the year 2017 as equal as possible to currently observed demand in the selected routes.

After changing the design of the subsidy, I recompute the equilibrium prices and quantities using the modified demand function for subsidized consumers, which looks as follows[9] One can already see that the change occurs in the price term; instead of multiplying it, now the subsidy is subtracting from it:

$$D_j^s(\mathbf{p}, \tau) = \sum_h N_h \frac{\exp\{\delta_j - \alpha_h(p_j - \tau)\}}{1 + \sum_k \exp\{\delta_k - \alpha_h(p_k - \tau)\}}$$

This has an important impact on the price elasticity of subsidized consumers, since the derivative of demand with respect to price is no longer affected by the subsidy. Under the current design, the subsidy rate decreases the derivative of demand with respect to price, since the effective price coefficient is $(1 - \tau)\alpha$. However, now τ does not impact the price coefficient. This makes demand more elastic at equal levels of price and quantity.

Using this new demand function, I compute the change in government expenditure, airline profits and consumer surplus from each of the different consumer groups to evaluate the optimal design of the subsidy. In the coming subsections I present the preliminary results of the initial counterfactual experiment.

[8] In case this amount is larger than price, the subsidy becomes equal to price, so that consumers cannot obtain a net monetary gain from buying a ticket.

[9] I drop the subscript of market m and time t for exposition purposes, but the functions are the same as in Section 3.

7.1 Change in equilibrium prices and quantities

Let's first look at how equilibrium prices change. To recompute the new equilibrium, I allow firms to choose optimally new prices in period -1. I register those prices and then I move back to period -2, and so on until period -5. I repeat this procedure until the new prices are exactly equal to the last prices chosen by firms, in a fixed-point procedure to recompute the new equilibrium. In Figure 7 I depict the mean prices along time to departure in the new equilibrium, and I compare them with the same statistic for observed prices. First of all, new prices are not very far away from observed prices, which is encouraging since the analysis can be seen as a local change in prices. This makes the necessary assumption that preference parameters such as price sensitivity do not change after the policy change more credible. The new equilibrium price is higher than the observed one for all periods until -2, and it becomes slightly lower than the observed one in the last period before departure. In the new equilibrium, firms expect consumers to anticipate their purchases due to the new design of the subsidy. Therefore, they can raise slightly early prices, because consumers are less happy to postpone to the last period (there is a less strong substitution effect with buying in the last period).

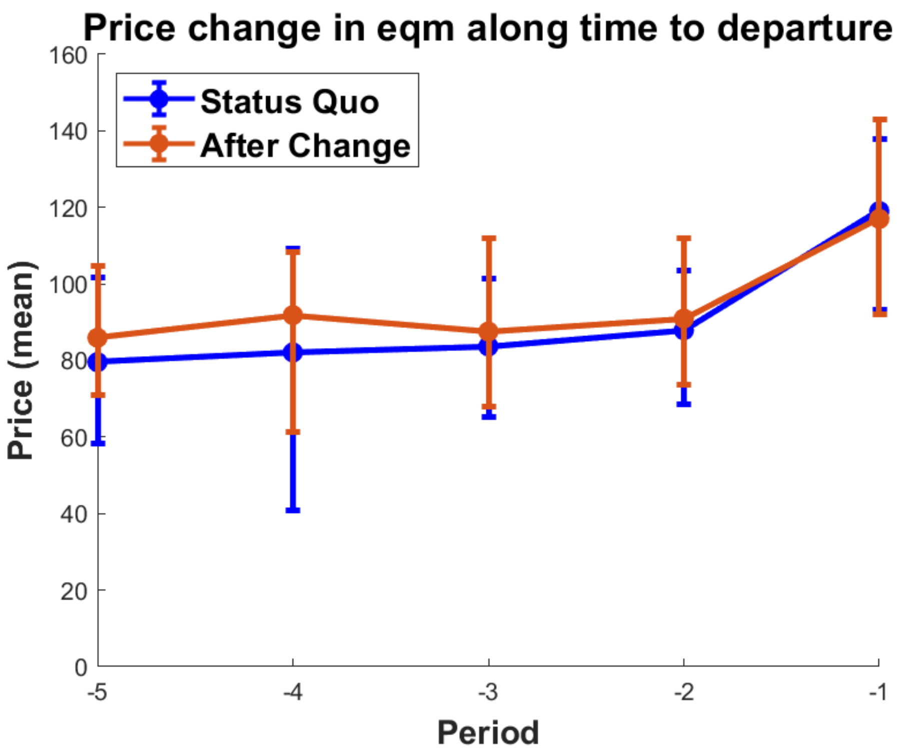

Figure 7: New mean prices along time to departure in new equilibrium after subsidy change

With respect to the new quantities after the change in the subsidy design, the main results can be seen in Figure 8. In this figure, I plot the share of total purchases along time-to-departure periods. The blue bars depict the share of purchases per period for the status quo situation, with the *ad valorem* subsidy design, whereas the orange bars depict the shares under the alternative unit subsidy design. It can be seen how under the current *ad valorem* setting, purchases are quite concentrated in the final period, whereas with the alternative design, purchases would be much more evenly distributed across the 5 periods. This is mostly due to the fact that under a unit design, the subsidy is constant in monetary units across time to departure, whereas in the current *ad valorem* design the subsidy in monetary units gets larger as the price increases towards departure, since the subsidy is a percentage of the price. In addition to this, under the *ad valorem* design, price sensitivity of consumers is directly impacted by the subsidy rate. This does not occur under a unit design. Therefore, in the latter situation, consumers are more price sensitive and prefer to buy earlier and avoid the high prices in the final periods.

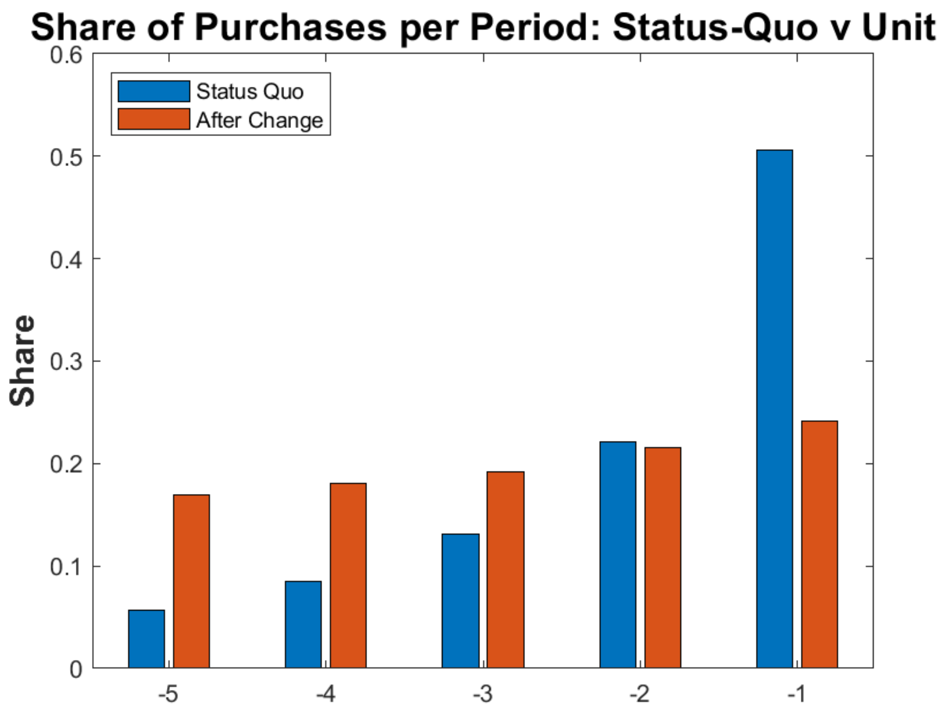

Figure 8: Distribution of share of purchases with subsidy change

Doing a similar analysis of shares of purchases across airlines, the results are depicted in Figure 9. One can see the effect of the increase in price sensitivity in the fact that the share of flag carriers, who normally charge more expensive prices, decreases significantly. On the other hand, the main low-cost competitor increases its share by a large factor (more than doubles it). This already hints at a desirable effect of the change in the policy design: consumers migrate from more expensive products (flag carriers), at the final periods (and higher prices), to low-cost products and buying earlier, and hence at lower prices.

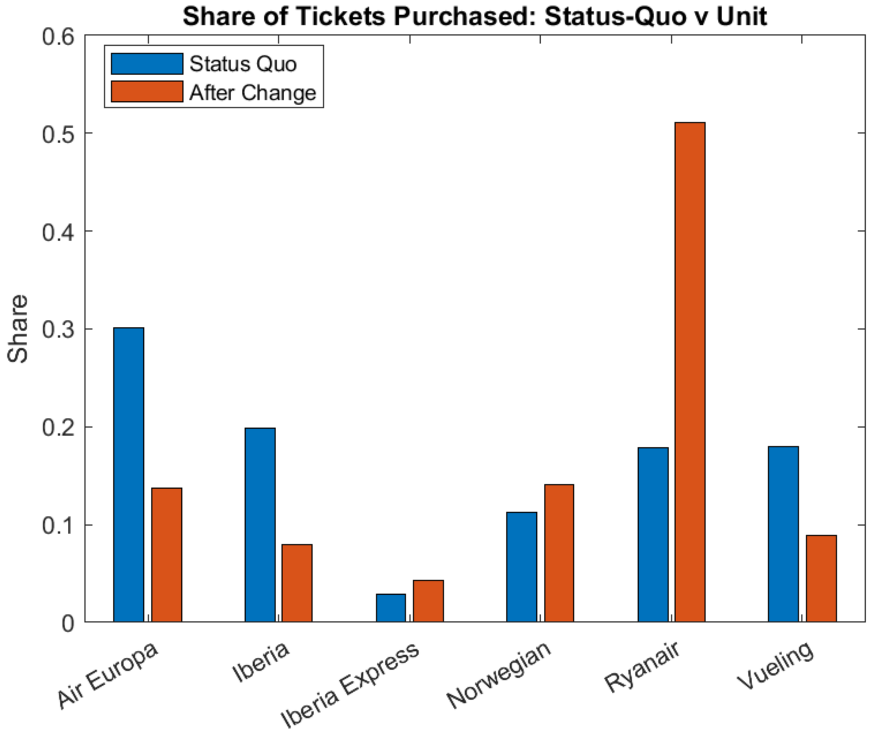

Figure 9: Distribution of share of purchases by airline with subsidy change

With respect to consumption patterns per income level, the change in share of demand for each group is quite small. Low income consumers reduce their share of consumption, whereas mid- and high-income consumers slightly increase their shares. This reflects the fact that prices are slightly higher after the change from *ad valorem* to unit design. Since low income consumers are the most price sensitive ones, their share of purchases decreases compared to the two other groups. This is depicted in 10.

7.2 Change in consumer welfare

To compute consumer surplus for each income group in each market, I use the log-sum formula corresponding to consumer surplus in logit demand settings (Train, 2009) to compute the change in consumer surplus due to the change in policy, both at aggregate level, at tourist and local level, and also disaggregating the local group by income level. The log-sum formula for consumer surplus is depicted below. This formula corresponds to the consumer surplus of income group h in market m, and it is computed by the sum across

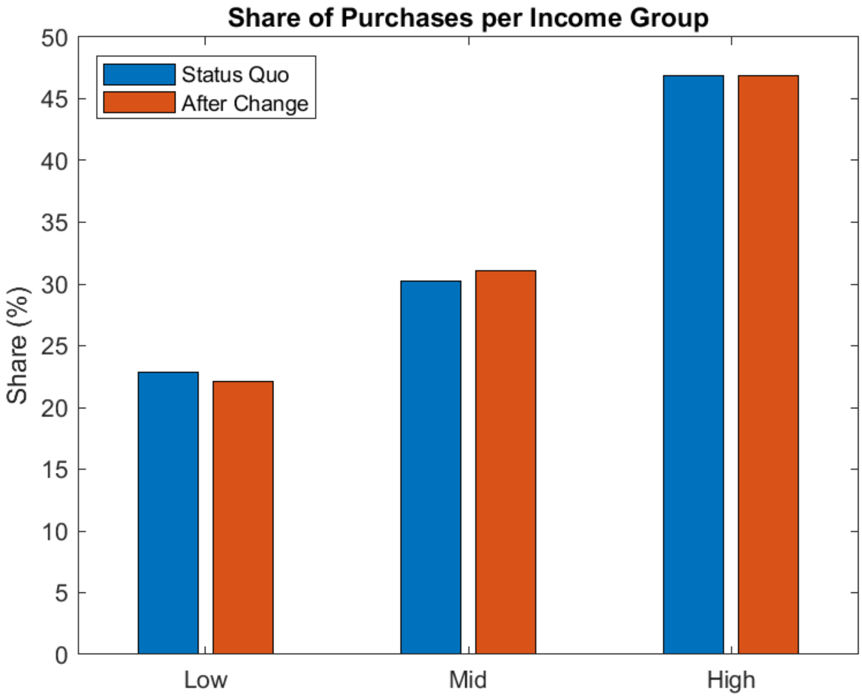

Figure 10: Distribution of share of purchases by income level with subsidy change

periods t of the Consumer Surplus obtained across consumption of products j and outside option.

$$CS_{hm} = \sum_{t=1}^{T} \left[\log \left(1 + \sum_{j} e^{\tilde{v}_{hjt}} \right) \right]$$

Figure 11 depicts the change in consumer surplus for each income type due to the change in subsidy design, for each period before departure. This figure is an average across all different markets. The subsidy change would only increase consumer surplus of high income consumers purchasing early. Low-income and mid-income consumers would suffer a decrease in their welfare, especially those buying in the final periods. This is due to the fact that the unit design does not protect consumers against high prices when they purchase in the final period.

7.3 Change in firm profits and government expenditure

The impact of the change in subsidy design on firm profits is depicted in Figure 12. It closely mirrors the change in shares depicted in Figure 9. Due to the different values of profits across airlines, I chose to depict the change of profits normalizing status quo to 1 for all airlines. First of all, it is important to notice how profits decrease for all airlines. This is mostly due to the large decrease in the share of purchases in the

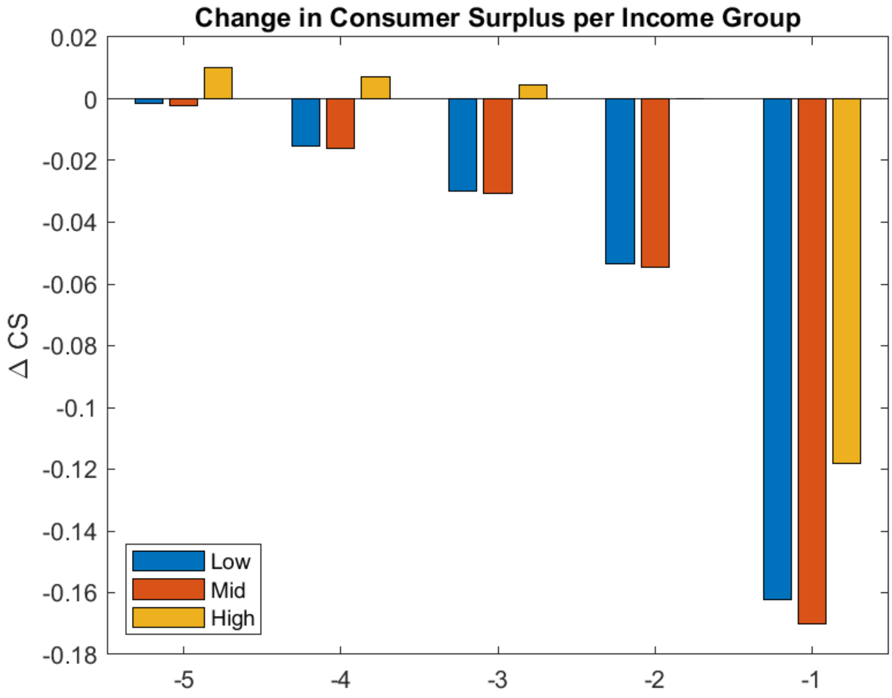

Figure 11: Change in Consumer Surplus for each income type after the policy change

final period, which are the most expensive by a margin. The main driver of the differential decrease in profits across airlines is the change in shares, since the change in prices is small. Because of this, the airlines which suffer a larger decrease in profits are the ones whose shares decrease the most, namely carriers belonging to the IAG group (Iberia, Iberia Express and Vueling), and Air Europa. The company which suffers less from the change in subsidy design is Ryanair, consistent with the effect on shares depicted above.

With respect to the change in government spending in the subsidy program, plotted in Figure 13, the change mirrors the change in consumption shares across time periods depicted in Figure 8. The change in the subsidy design would actually increase government expenditure in the periods far away from departure (periods -5 to -3, which correspond to more than 30 days before departure). This is consistent with the increase of purchases happening further away from departure. Importantly, in the final period (which corresponds to the last 2 weeks before departure), government spending would be massively reduced as a consequence of the change in the subsidy design. This is a combination of two effects. Firstly, as a result of the change in design there would be a lower share of purchases happening in this period. Secondly, under the original *ad valorem* design, each transaction forces the government to a large amount of subsidy, since it is a proportion of the price, which is quite high in the final period. Under the new design, the cost per transaction for the government is independent of the price posted by airlines, and constant across time to

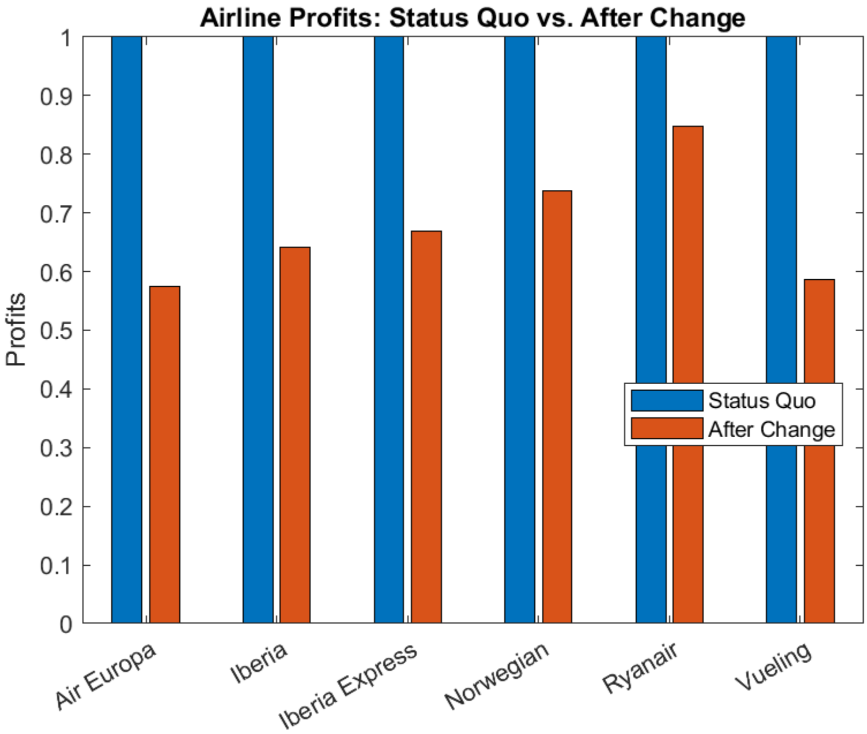

Figure 12: Change in airline profits with subsidy change

departure.

8 Conclusion

I show that price discrimination is a relevant factor when analyzing the consequences of different subsidy (or tax) designs. Using an empirical setting with intertemporal price discrimination—the Spanish airline industry—I compare *ad valorem* and unit designs and show that the former drives consumers to purchase a larger share of higher-quality, more expensive products, raising government spending relative to uniform pricing. This also has distributional implications across consumer groups.

Methodologically, the paper develops a dynamic discrete choice model in which consumers are forward-looking and choose both *whether* and *when* to buy along the booking horizon. Estimation follows a Hotz–Miller CCP approach tailored to intertemporal choices and addresses zero-purchase observations via a selection stage before a BLP-style random-coefficients estimation with instruments. On the supply side, I recover period-specific marginal costs from a multiproduct oligopoly model of intertemporal pricing and use the estimated demand and costs to compute counterfactual equilibria under a unit subsidy design

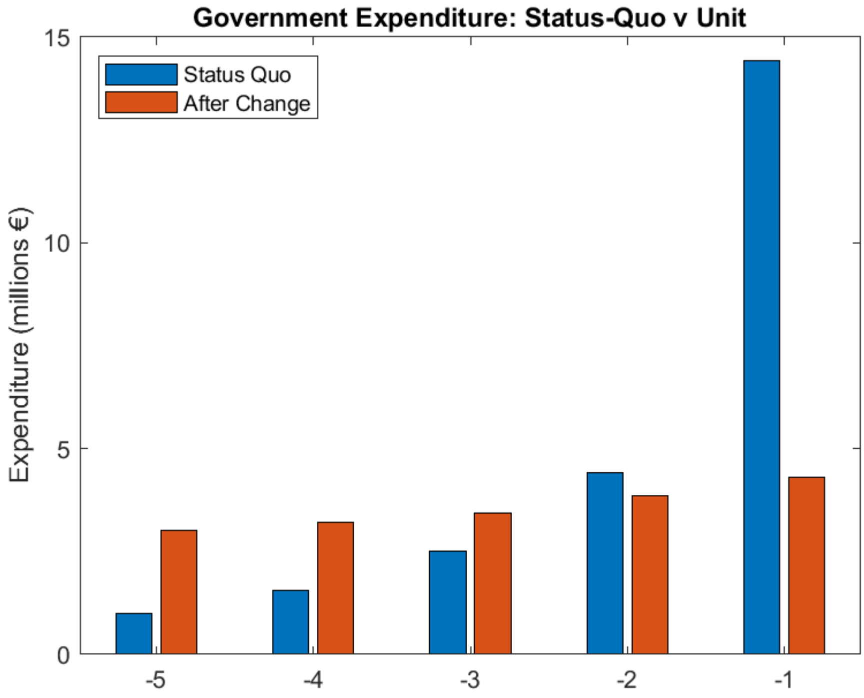

Figure 13: Distribution of government spending with subsidy change

calibrated to preserve access.

The mechanism is straightforward. With rising prices over the booking horizon, an *ad valorem* transfer both scales down the effective price coefficient and magnifies the monetary subsidy precisely where fares are highest. This weakens incentives to purchase early and concentrates subsidized demand in the final period. By contrast, a unit transfer leaves price sensitivity intact and keeps the per-transaction subsidy constant across periods, realigning incentives toward earlier, cheaper purchases. In the model-based counterfactual, replacing the *ad valorem* design with a unit subsidy (32.46 € in the baseline calibration) spreads purchases more evenly over time, shifts demand toward lower-priced carriers, and reduces government expenditure, with savings concentrated in the final period. Airline profits fall, especially for higher-price incumbents, reflecting reallocation and reduced scope to capture transfers; access is preserved by construction.

Three policy principles emerge for markets with intertemporal price discrimination: (i) avoid tying subsidies to posted prices; (ii) if the policy objective is access rather than quality upgrading, a unit design better targets the extensive margin without steering purchases toward expensive periods; and (iii) distributional and incidence effects depend critically on timing—unit designs preserve price sensitivity, restoring competitive pressure on late-period pricing and limiting pass-through of public funds into markups.

Limitations guide future work. The current equilibrium abstraction from rationing risk models capacity in reduced form; incorporating capacity constraints and inventory controls is a natural extension. Completing the consumer-surplus accounting by income group is also on the agenda. Nonetheless, across environments where timing or quality tiers interact with market power—air travel, hotels, rail, and related perishable or durable settings—the central conclusion is robust: when firms practice intertemporal price discrimination, a unit (specific) subsidy can achieve the same access at markedly lower fiscal cost than an *ad valorem* design, while curbing rent capture and better aligning policy intent with market outcomes.

References

[1] Adachi, T., & Fabinger, M. (2021). Pass-Through and the Welfare Effects of Taxation under Imperfect Competition: A General Analysis (No. e-21-003).

[2] Aguirregabiria, V. (2024). Empirical industrial organization: models, methods, and applications. University of Toronto, Preliminary version.

[3] Auerbach, A. J., & Hines, J. R. (2001). Perfect taxation with imperfect competition.

[4] Barwick, P. J., Kwon, H. S., & Li, S. (2024). Attribute-based subsidies and market power: an application to electric vehicles (No. w32264). National Bureau of Economic Research.

[5] Berry, S., & Jia, P. (2010). Tracing the woes: An empirical analysis of the airline industry. *American Economic Journal: Microeconomics*, 2(3), 1–43.

[6] Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63(4), 841–890.

[7] Berry, S., Levinsohn, J., & Pakes, A. (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of Political Economy*, 112(1), 68–105.

[8] Betancourt, J. M., Hortaçsu, A., Öry, A., & Williams, K. R. (2024). Dynamic Price Competition with Capacity Constraints (No. w32673). National Bureau of Economic Research.

[9] Botelho, V. (2025). Optimal Subsidies in Capacity-Constrained Essential Services. Job Market Paper.

[10] Calzada, J., & Fageda, X. (2012). Discounts and public service obligations in the airline market: lessons from Spain. *Review of Industrial Organization*, 40, 291–312.

[11] Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press.

[12] Dana Jr, J. D., & Williams, K. R. (2022). Intertemporal price discrimination in sequential quantity–price games. *Marketing Science*, 41(5), 966–981.

[13] D'Annunzio, A., & Russo, A. (2022). Welfare-Enhancing Taxation and Price Discrimination. *CESifo Working Papers*, No. 10007-2022.

[14] De Groote, O., & Verboven, F. (2019). Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *American Economic Review*, 109(6), 2137–2172.

[15] Dubé, J.-P. H., Hortaçsu, A., & Joo, J. (2020). Random-Coefficients Logit Demand Estimation with Zero Valued Market Shares. *Becker Friedman Institute Working Papers*, No. 2020-13.

[16] Fageda, X., Jiménez, J. L., & Valido, J. (2017). An empirical evaluation of the effects of European public policies on island airfares. *Transportation Research Part A*, 106, 288–299.

[17] Fageda, X., Jiménez, J. L., & Valido, J. (2016). Does an increase in subsidies lead to changes in airfares? Empirical evidence from Spain. *Transportation Research Part A*, 94, 235–242.

[18] Hotz, V. J., & Miller, R. A. (1993). Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies*, 60(3), 497–529.

[19] Laffont, J.-J., & Tirole, J. (1993). *A Theory of Incentives in Procurement and Regulation.* MIT Press.

[20] Lazarev, J. (2025). The welfare effects of intertemporal price discrimination: an empirical analysis of airline pricing in US monopoly markets. *Revise & Resubmit, American Economic Review.*

[21] Marra, M. (2025). A Market for Airport Slots. *Available at SSRN.*

[22] Muehlegger, E., & Rapson, D. S. (2022). Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California. *Journal of Public Economics*, 216, 104752.

[23] Suits, D. B., & Musgrave, R. A. (1953). *Ad valorem* and unit taxes compared. *The Quarterly Journal of Economics*, 67(4), 598–604.

[24] Train, K. E. (2009). *Discrete Choice Methods with Simulation.* Cambridge University Press.

[25] Weyl, E. G., & Fabinger, M. (2013). Pass-through as an economic tool: Principles of incidence under imperfect competition. *Journal of Political Economy*, 121(3), 528–583.

[26] Williams, K. R. (2022). The welfare effects of dynamic pricing: Evidence from airline markets. *Econometrica*, 90(2), 831–858.