Welfare Consequences of Upgrades: Evidence from the Airline Industry*

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Abstract

Using upgrades - fees that customers pay to access a premium quality product after the purchase of a regular one - can significantly affect consumer welfare. On the one hand, regular consumers benefit from potentially accessing the monopolist's higher-quality goods at a discounted price. On the other hand, the monopolist will seek to capture surplus from these gains from trade by offering a different price menu for all goods. Whether consumer welfare will rise or fall when a firm introduces upgrades will depend on the relative magnitudes of these two effects. The aim of this research is to disentangle these two effects in the context of an international airline that gives Economy Class passengers the option to pay an additional fee to upgrade to Business Class. I develop and estimate a model of airline pricing in order to assess the effects of upgrades via counterfactual simulations. I show that the upgrade option improves the allocation of passengers across cabins over time, which leads to an increase in consumer and producer welfare of 1.5% and 2% respectively.

1 Introduction

Offering upgrades is a popular practice in industries characterized by multiproduct offerings and limited capacity. Airlines, freight transport providers, car rental companies and

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hotels offer products of various quality and allow customers to access premium quality products either with a retail sale or with an upgrade.

Firms complement the retail sales channel with upgrades in order to sequentially price discriminate and manage limited inventory. However, the introduction of this new sales channel has ambiguous effects on total welfare. On one hand, the availability of the upgrade option provides the seller with extra flexibility in selling products, resulting in a non-negative change in producer surplus. In particular, through upgrades, firms can find customers who value premium products below the listed price among those who already hold a regular product. According to theoretical research, this may improve allocative inefficiencies by reducing mismatch between supply and demand (Gallego and Stefanescu, 2009; Cui, 2017). Moreover, existing evidence suggests that airlines' revenues could increase after the introduction of upgrade options (Cui et al., 2019). On the other hand, the effect on customers is less straightforward. Upgrades increase the welfare of consumers who can enjoy premium products at discounted prices. However, introducing the upgrade option modifies the seller's pricing problem, potentially influencing the price menu with ambiguous effects on consumer welfare. Existing theoretical studies (Varian, 1985; Aguirre et al., 2010; Bergmann et al., 2015) do not consider sequential price discrimination strategies featuring dynamic multiproduct offering and limited inventory, thus leaving the effect of upgrades on consumers an open question.

This paper studies how introducing upgrades affects welfare in the context of the airline industry. In particular, I analyze proprietary data from an international airline[1], that employs upgrades to allocate premium cabin seats. The data shows how the airline uses upgrades and allows me to estimate a structural model. The empirical analysis shows that upgrades are a relevant sales channel for premium products and that the airline employs them for price discrimination. After estimating the structural model, I am able to quantify the effect of upgrades on welfare through counterfactual simulation. Results indicate that, on average, both consumers and the monopolist benefit from the upgrade option.

There are at least two compelling reasons to study upgrades in the airline industry. Firstly, the airline sector stands as one of the largest industries globally, contributing

[1] The identity of the airline will be kept confidential. In terms of size, in the year 2018, the airline studied in this paper made \$13B revenues. As a benchmark, American Airlines made \$43B (macrotrends).

approximately 5% to the world GDP and 4.2% to the US GDP (IATA, 2018). Secondly, upgrades are extensively used in the industry, with upgrade programs being implemented by all major international airlines (see for example United Airlines, Delta Airlines, American Airlines, China Southern Airlines, Lufthansa and KLM).

In this paper, I use a comprehensive transaction-level dataset obtained from the revenue management department of an international airline. The dataset contains all the 268,035 ticket purchases made over 1,600 flights, connecting two monopolistic routes, during the period between September and December 2018. For each ticket in the dataset, I have access to information such as the final price paid, timing of purchase and cabin class (Economy, Premium Economy or Business Class). Notably, the dataset shows whether customers in lower cabins upgrade to premium cabins and, if so, at which price.

This dataset enables me to find new evidence about upgrades and validate well-established facts about retail sales in the airline industry. Regarding upgrades, I am able to establish two significant findings. Firstly, upgrades serve as a valuable sales channel, with the airline utilizing them to sell 16% of their premium seat tickets, resulting in 2% of total revenues. Second, the airline uses upgrades to sell higher quality seats at a discounted price. On average, customers who upgrade to premium cabins save 15% off the retail price of those cabins. This is in line with the theory of sequential price discrimination, where the firm, firstly, selects demand through retail sales and then sells the high-quality product again at lower prices. On the other hand, the retail pricing data exhibits characteristics consistent with those described in the economics literature on airline pricing. In fact, consistently with Williams (2022) and Lazarev (2013), the airline engages in dynamic pricing to practice intertemporal price discrimination among customers. Those who purchase their tickets early have lower willingness to pay for travel compared to those who purchase last minute. Furthermore, in line with Aryal et al. (2023), the airline practices intratemporal price discrimination by offering products of different qualities at various prices to segment customers based on their value for comfort.

In order to measure changes in consumer welfare resulting from the upgrade sales channel, I construct a structural model of demand and supply. On the demand side, I expand upon the model developed by Aryal et al. (2023). Customers randomly enter the airline ticket market and, upon arrival, make decisions regarding purchasing Economy or

Business Class tickets, or not flying at all. If customers buy an Economy Class ticket, they have the option to upgrade to Business Class in the last two days before departure. When modeling customer's upgrade option, I make two assumptions. Firstly, I impose that customers do not anticipate the possibility of an upgrade. While this assumption simplifies the problem solution and aligns with much of the prior literature[2], it rules out strategic thinking on the part of consumers. Additionally, I assume customers' inattention. Specifically, the airline sends a notification (e.g., an email) to all Economy Class ticket holders two days before departure, but only a fraction of them actually pay attention to the notification itself. This assumption enhances the model's credibility in two ways. Firstly, it mirrors how, in the airline industry, firms offer upgrades (as reported by Tripadvisor, see also Appendix A.1 for an example). Secondly, it aligns with customers' response patterns to notifications in the travel industry, where only 20% of customers open traveling related emails (as reported by Constant Contact and campaignmonitor.com).

On the supply side, the airline solves a two-period pricing problem with capacity constraints for both Economy and Business Class. In both periods, the airline sells Economy and Business Class seats retail. In the last period and upon availability in premium cabin, the airline sells upgrades to customers holding an Economy Class ticket from the initial period. As a result, the airline's dynamic programming problem encompasses multiple products and upgrades. The model allows me to capture crucial aspects of airline price discrimination strategies, including intertemporal (dynamic pricing), intratemporal (regular vs premium cabin) and sequential (upgrades) price discrimination.

To account for price differences across flights and over time, I specify the model with random coefficients. After identifying the model at the flight-level, I estimate it at the aircraft-route-level[3]. By assuming optimal price choices alongside demand-side restrictions, I am able to identify customers' preferences and arrival rate over time. I estimate the model using a simulated method of moments, where I match the distribution of prices and ticket sales. The estimated parameters allow the model to approximate the observed distributions of prices and quantities.

Using these estimates, I conduct counterfactual simulations to examine how the up-

[2] For example, Williams (2022) and Aryal et al. (2023); one relevant exception is Lazerev (2013), which allows consumers to strategically time their initial ticket purchase.

[3] Focusing on route-level demand is consistent with practices in the industry (see IATA).

grade option affects pricing decisions and welfare. Firstly, I discuss the impact of upgrades on pricing decisions and their interaction with capacity constraints conditional on the demand shock. On one hand, irrespective of capacity constraints, the airline uses upgrades to sequentially price discriminate initial period customers, thereby affecting initial period prices. In particular, since the airline anticipates that some initial period Economy Class ticket holders will upgrade to Business Class, the opportunity cost of raising initial period premium cabin prices decreases. On the other hand, how the upgrade option interacts with capacity constraints, and how it affects the airline pricing problem, depends on the demand shock. In the case of a low demand shock in the initial period, the airline experiences few sales in both cabins, and it uses the upgrade option only to sequentially price discriminate initial period customers: this alone does not affect last period prices. On low-value flights, then, the upgrade option increases welfare by enabling the airline to fill empty seats in premium cabin and granting customers access to premium cabin at a discount. On the other hand, in case of large and positive initial period demand shocks, the probability of Business Class selling out in the initial period is large and the airline potentially misses out on high-value sales, from high-value travelers, in the last period. In such a scenario, the airline uses the upgrade option as a costless way to reduce this probability. By anticipating that high-value customers who have bought Economy Class in the initial period can upgrade in the final period, the airline further increases initial period Business Class prices as a way to restrict the number of its retail sales in the initial period. Furthermore, beyond distorting initial period prices, the upgrade option also affects prices in the last period due to its interaction with capacity constraints. In fact, upgrading customers compete with retail buyers for Business Class in the final period. On high-value flights, then, the upgrade option increases welfare by reducing the number of early sellouts in premium cabin and improving the efficiency of seats allocation over time.

Secondly, I quantify the welfare effects of the upgrade option for both travelers and the airline. From a welfare standpoint, introducing the upgrade option has a positive impact on both consumer and producer surplus, thereby increasing efficieny. Overall, consumer surplus increases by an average of 1,227$ (1.5%) per flight, and producer surplus increases by an average of 1,553$ (2%) per flight, which is significant in a low-margin industry. The main driver of the increase in consumer surplus is the utility gain experienced by customers who choose to upgrade, thereby accessing Business Class at a discount. This compensates the loss in utility due to higher retail prices of the premium product. Concurrently, the increase in producer surplus is driven by the revenue generated from upgrade fees, which compensates fewer sales resulting from higher prices.

Literature review

The research question of this paper is connected to the recent literature in operations management that focuses on upgrades. Most papers study how sellers can benefit from upgrades both theoretically (Gallego and Stefanescu, 2009; Cui et al., 2018; Cui and Shin, 2018) and empirically (Cui et al., 2019; Yilmaz et al., 2017). In particular, Cui et al. (2019) study the effects of specific upgrade products known as add-ons, which require the purchase of a regular product before accessing the premium product, in a quasi-experiment within the airline industry. I extend this literature in at least two ways. Firstly, none of these studies empirically quantifies consumer welfare changes resulting from upgrades. Secondly, this paper incorporates the possibility of customer inattention to the upgrade option, modeled as a behavioral parameter following a similar approach to Gabaix (2019).

This paper extends the empirical literature studying how price discrimination affects welfare. Most empirical papers focus on either intratemporal (Leslie, 2004; Crawford and Shum, 2007) or intertemporal price discrimination (Lazarev, 2013; Cho et al., 2018). Only Chandra (2020) and Aryal et al. (2023) consider both aspects. I contribute to this research by developing an empirical model that allows me to consider upgrades as an additional sales channel through which the airline engages in sequential price discrimination.

Additionally, this paper builds on recent airline studies, including Dana et al. (2022), Aryal et al. (2023), Williams (2022), Lazarev (2013), Li et al. (2014). Williams (2022) and Lazarev (2013) analyze the effects of dynamic pricing on consumers; Li et al. (2014) investigate customers' incentives to delay ticket purchases, and Aryal et al. (2023) examine a monopolist selling vertically differentiated products with dynamic pricing. Meanwhile, Dana et al. (2022) consider a dynamic pricing inventory control problem. However, these papers do not take into account the role of upgrades in sequential price discrimination and inventory management, overlooking important factors that influence pricing decisions.

I build on on the methods used by Williams (2022) and Aryal et al. (2023) in modeling and estimation. In particular, Williams (2022) considers a single product monopolistic airline engaging in dynamic pricing. Aryal et al. (2023) expand this framework, by investigating a firm combining dynamic pricing with vertical product differentiation. My paper further enriches the setting described by Aryal et al. (2023), by allowing the airline to sell upgrades. In terms of demand and supply modeling, my framework introduces a novel decision problem on both the demand side, as customers decide whether to upgrade, and the supply side, as the firm optimally chooses the upgrade price. In terms of identification strategy, I adopt the approaches of both Williams (2022) and Aryal et al. (2023) by leveraging supply-side constraints to argue separate identification of arrival rates and customer preferences. As for estimation, I follow Aryal et al. (2023), by implementing a simulated method of moments, within a random coefficient demand model. In terms of findings, my paper is closely related to Williams (2022). Specifically, Williams (2022) demonstrates that the airline uses dynamic pricing to intertemporally price discriminate and to manage inventory, by reserving capacity for high-value customers in later periods. Similarly, my results indicate that upgrades do not only work as a way to price discriminate, but also, conditional on the size of the demand shock, can serve as a tool to improve inventory allocation over time.

2 Data and descriptive evidence

This project uses a new transaction-level data from an international airline, that sells premium cabin seats with upgrades in the last two days before departure. The dataset contains information on both upgrades and retail sales. Analysis of the upgrade data reveals two facts: firstly, upgrades are a relevant sales channel and, secondly, the airline employs upgrades to sell premium cabin seats at a discounted price. Examination of the retail price data shows the airline's dynamic pricing strategy across multiple products. Overall the data aligns with the theory of price discrimination, as the airline uses intertemporal and intratemporal price discrimination along the retail channel, while engaging in sequential price discrimination with upgrades.

2.1 Data description

The dataset contains the universe of ticket purchases from all the 1,600 flights operating on two monopolistic routes between September and December 2018, for a total of 268,035 ticket purchases. While I am unable to disclose the specific routes, one route is domestic and has a similar duration to a flight from New York to Miami (approximately 3 hours), while the other route is international and has a duration similar to a flight from New York to Mexico City (approximately 6 hours). For each transaction in the dataset, there is both traveler and product information. The traveler information includes gender, age, reason for traveling (whether for business or leisure) and flyer-ID (whether travelers are members of loyalty programs). The product information includes ticket price, timing of purchase and the final traveling class (Economy, Premium Economy or Business Class)[4]. In the case of an upgrade, the dataset records the upgrading fee. Additionally, the product information displays flight characteristics such as the day and time of departure, as well as the aircraft model.

2.2 Quantity of upgrades

The airline sells a large fraction of seats with upgrades in the last two days before departure: this generates substantial revenues. I provide two pieces of evidence to support this claim. Firstly, I present the aggregate number of transactions and revenues generated by upgrades in relation to retail sales. Secondly, I analyze the seat allocation over time, taking into account both retail and upgrade sales.

Compared to retail sales of premium cabins (Premium Economy and Business Class), upgrades serve as a relevant sales channel in terms of both transactions and revenues. According to Table 1, a large group of travelers chooses to fly in premium cabins because of an upgrade, and the fees associated with these upgrades contribute significantly to the overall revenues of the airline. Over all premium cabins' transactions, 29% of Premium Economy and 10% of Business Class seats are sold with an upgrade. Considering revenues, upgrading fees account for 17% of Premium Economy and 5% of Business Class revenues.

[4] The dataset also contains tickets' fare, which encompasses other features of the ticket, such as flexibility or refundability, potentially impacting ticket quality and the final price paid. However, discussions with the airline revealed that this information is not accurate, thus is not utilized in this paper. For the purposes of this study, I consider all tickets within a cabin to have the same quality.

In aggregate, 16% of travelers fly in premium cabins because of an upgrade. These upgrade fees account for 6% of premium cabins revenues, and nearly 2% of total revenues.

Furthermore, when considering sales over time, the airline allocates a large number of seats in premium cabins in the last two days before departure. Figure 1 shows how the airline sells seats in premium cabins over time, by distinguishing between retail and upgrade sales. In the last two days before departure, the number of seats allocated in Premium Economy Class is five times the number of seats allocated with a retail sale. Similarly for Business Class, where as many retail sales as upgrades take place in the last two days before departure.

2.3 Price of upgrades

Pricing data shows that accessing premium cabin via an upgrade is cheaper than via a retail purchase. I provide two pieces of evidence to support this claim. Firstly, I analyze the time series of prices to access premium cabins. Secondly, I discuss the results of conditional mean regressions.

Figure 2 provides visual evidence of the discount offered through upgrades. It compares the average final price paid to access premium cabins for any time of the initial ticket purchase. Customers flying in Premium Economy and Business Class with an upgrade consistently enjoy discounts compared to the retail price.

Similarly, specification (1) examines the extent of these discounts. It compares the final prices paid to access premium cabin through retail sales and with an upgrade.

$$P_{\mathrm{i}} = \alpha + \beta_{\mathrm{up}} \mathbb{I}\{\text{upgrade sale}\}_i + \epsilon_i \tag{1}$$

where P_{i} is ticket i's final price paid to access premium cabin. The coefficient α represents the average final price for accessing premium cabin through retail purchase, whereas β_{up} measures the savings (compared to the average final retail price) offered to travelers who access premium cabins through upgrades.

I show coefficients' estimates separately for Business and Premium Economy Class. Table 2 shows that customers who upgrade to Business Class spend, on average, 13% less than if they had purchased a Business ticket at retail price. Similarly, Table 3 indicates that customers who upgrade to Premium Economy save, on average, 18% off the average retail price. Because final paid prices might depend on the level of already sold capacities and on the time of initial purchase, selection might be of a concern for specification (1). In particular, large absolute values of β_{up} might be due to variation in prices across flights with different level of sold capacity in the last two days before departure or at the time of the initial purchase. Similarly, large absolute values of β_{up} might capture variation in prices due to variation in the time of initial purchase. I control for these effects, by adding levels of unsold capacities, time of the initial purchase and flight fixed effects as control variables to regression (1). In Appendix A.2, I show that estimation results are robust even after controlling for these effects.

2.4 Airline's pricing strategies and price discrimination

Evidence from retail prices, along with the one from the upgrade channel, shows that airline pricing strategies are consistent with various degrees of price discrimination extensively discussed in the literature. In particular, the airline engages in intertemporal, intratemporal and sequential price discrimination.

The airline allocates the majority of its seats through the retail channel. Along this channel, it implements pricing strategies consistent with well-established theories of price discrimination discussed in the existing literature. Data presented in Table 1 indicates that the airline sells 95% of its seats via the retail channel, which contributes up to 98% of total revenues. Figure 3 displays the airline's pricing patterns over time, providing support for pricing strategies that align with the airline economics literature. This includes the use of dynamic pricing to intertemporal price discriminate consumers. Previous studies such as Williams (2022) and Lazarev (2013) have highlighted that customers who purchase tickets earlier in the booking horizon tend to exhibit a lower willingness to pay for travel compared to those making last-minute purchases. Furthermore, similarly to the analysis of Aryal et al. (2023), the airline employs intratemporal price discrimination by offering distinct levels of comfort at distinct prices. In this way, the airline caters to different customer segments based on their willingness to pay and value for comfort.

On the other hand, customers accessing premium cabin with a discount, after their initial retail purchase, supports the theory of sequential price discrimination, discussed in

Cui et al. (2019). In the first stage of retail sales, the airline sorts customers in different cabins based on their preferences. For instance, customers with a lower willingness to pay prefer to purchase an Economy Class ticket rather than a Business Class ticket. However, the marginal customer in Economy Class would have bought Business Class had it been more affordable. Therefore, after the retail stage, the airline offers these marginal Economy Class customers the opportunity to upgrade to higher cabin at a discounted price, effectively using upgrades as a sequential screening tool.

3 Model

In this section, I present a model that captures the supply and demand dynamics of the airline industry. On the supply side, I consider a capacity constrained monopolistic airline which optimally chooses prices for Economy and Business Class tickets any day t of the booking horizon. For simplicity, $t \in \{0, 1\}$, with $t = 0$ being the initial period of the booking horizon, and $t = 1$ being the departure day. Additionally, in $t = 1$, the airline sells upgrades, allowing those who bought an Economy Class ticket in $t = 0$ to pay a fee and access the Business Class. I assume full integration of firm's pricing decisions, meaning that prices are determined by solving a dynamic programming problem that considers multiple cabins and upgrades simultaneously. This supply model reproduces relevant features of the airline's price discrimination strategies, including intertemporal, intratemporal and sequential price discrimination. On the demand side, customers randomly enter the market for airline tickets and, upon arrival, make a decision regarding whether to purchase an Economy or a Business Class ticket or, alternatively, not to fly at all. I assume that customers do not expect the possibility of an upgrade when making their purchase decision. In $t = 1$, when the airline offers the upgrade possibility, only a fraction of customers is attentive to the offer and then consider whether to upgrade or not. This demand specification embeds uncertainty in the number of travelers shopping for a ticket, heterogeneity in preferences and inattention to the upgrade option.

3.1 Demand

The demand model is developed in two steps. First, following Williams (2022) and Aryal et al. (2023), I describe the retail sales market for airline tickets: how consumers arrive to the market and how they choose between buying Economy, Business Class or not flying at all. Then I describe how Economy ticket holders decide to upgrade.

Along the retail channel, firstly, customers randomly arrive to the market of airline tickets, then, without expecting the upgrade option, they make their retail purchase decision. Customers arrive to the market of airline tickets in each period $t \in \{0, 1\}$ of the booking horizon, starting from the initial period $t = 0$ until the departure day $t = 1$. In each period t, a number N_t of customers arrive, following a Poisson process with parameter λ_t. Similarly as in Williams (2022) and Aryal et al. (2023), customers have discrete types: they either have a probability θ_t of flying for business-related reasons (H-types), or a probability of $1 - \theta_t$ of flying for leisure (L-types). Once customers enter the market, they maximize their utility by choosing between an Economy or Business Class seat or deciding to exit the market. Customers make this decision, by not expecting the possibility of an upgrade. As in Aryal et al. (2023), customers differ in willingness to pay and value for comfort[5], and goods are vertically differentiated: all customers prefer Business to Economy Class seats when they are sold at the same price. By defining j as the product choice, p_{EC} as the price for Economy Class and p_{BC} as the price for Business Class, I specify the utility function for individual i and type k as:

$$u_{ikj} = \begin{cases} v_{ik}\xi_{ik} - p_{BC} & \text{j= Business Class Seat} \\ v_{ik} - p_{EC} & \text{j= Economy Class Seat} \\ 0 & \text{j= } \emptyset \end{cases} \tag{2}$$

where the utility of not flying ($j = \emptyset$) is normalized to 0. In the above specification (2), v_{ik} represents the willingness to pay for traveling and $\xi_{ik} > 1$ represents the value for comfort from flying in Business Class. I assume that v_{ik} and ξ_{ik} are random variables independently drawn from type-specific distributions $F_v^{kt}(\cdot)$ and $F_\xi^{kt}(\cdot)$, which are allowed

[5] Demand shocks are a measure of the desirability of a flight. For instance, if there is a conference at the destination, business type customers are likely to have high WTP for flights departing before the conference, on the other hand, around Thanksgiving leisure type customers are willing to pay more as their need for vacation.

to vary over time.

Travelers are naive and do not expect the upgrade option: in specification (2), utility does not include the future possibility of being upgraded. This assumption is in line with recent revenue management literature which states that, in the long run, "[...] it is unlikely that customers will adapt strategically to upgrades" (Gallego et al., 2009). Additionally, this assumption simplifies the problem, since it does not require customers to form expectations about future prices. Since customers do not expect the upgrade option, its only implication is a new decision problem in period $t = 1$ for those customers who had bought an Economy Class ticket in $t = 0$ and are attentive to the notification of the airline. I assume only a fraction α_k of Economy Class ticket holders of type k pays attention to the notification sent by the airline. For these attentive Economy Class ticket holders, the decision to upgrade reduces to a comparison between the utility of flying in Business Class with an upgrade and the utility of flying in Economy, given the retail price originally paid for an Economy ticket. Therefore, customer i, who purchased an Economy Class ticket in period $t = 0$ at $p_{0,EC}$, chooses to upgrade if and only if the following inequality holds:

$$\underbrace{\xi_i v_i - p_{0,EC} - p_{UP}}_{\text{utility from flying in Business Class after an upgrade}} \geq \underbrace{v_i - p_{0,EC}}_{\text{utility from flying in Economy Class}} \tag{3}$$

with p_{UP} being the upgrade fee. Based on expression (3), from the airline's point of view, the probability of buying an upgrade, conditional on an Economy Class ticket purchase in period $t = 0$ is given by the following expression:

$$s_{UP}(p_{0,EC}, p_{0,BC}, p_{UP}) = \int \int \mathbb{1}\{\xi v - p_{UP} \geq v\} d\tilde{F}_v d\tilde{F}_\xi \tag{4}$$

where $\tilde{F}_v(x) = \mathbb{P}\Big(v \leq x | v - p_{0,EC} \geq \max\{\xi v - p_{0,BC}, 0\}\Big)$ and $\tilde{F}_\xi(y) = \mathbb{P}\Big(v \leq y | v - p_{0,EC} \geq \max\{\xi v - p_{0,BC}, 0\}\Big)$. In summary, I represent the whole demand process for an individual flight as vector Ψ:

$$\Psi = \left(\left\{\{F_v^{kt}(\cdot), F_\xi^{kt}(\cdot), \alpha_k\}_{k \in \{H,L\}}, \lambda_t, \theta_t\right\}_{t \in \{0,1\}}\right). \tag{5}$$

3.2 Supply

For any flight, the airline solves a dynamic multiproduct pricing problem with capacity constraints. The problem is dynamic as the airline is active in two periods: $t = 0$, the initial period and, $t = 1$, the last period. At the beginning of any period t, the airline sets prices for both Economy and Business Class, denoted as $p_{t,EC}$ and $p_{t,BC}$, respectively. Additionally, in the last period $t = 1$, the airline also sets p_{UP}, which allows customers who had bought an Economy Class ticket to upgrade to Business Class. When setting prices, the airline faces capacity constraints: the total number of Economy and Business Class flying passengers cannot exceed the total number of seats available in Economy and Business Class, represented by c_{EC} and c_{BC}, respectively. If in any period t, the airline sells more tickets than the available left capacity ($c_{t,EC}$ and $c_{t,BC}$), it reimburses the extra tickets. I assume that the airline chooses the upgrade price simultaneously with the retail prices. However, firstly, the firm allocates retail passengers, then, if there is left capacity in premium cabin, it sells upgrades. In both periods *t=0* and *t=1*, the airline chooses prices optimally based on the observed demand shock (Ψ_t) and the number of residual capacities in both cabins ($c_{t,EC}$ and $c_{t,BC}$). In $t = 1$, because of the presence of upgrading travelers, the firm also takes into account prices and demand shocks realized in $t = 0$.

In period $t = 0$, the airline chooses $p_{0,EC}$ and $p_{0,BC}$, by solving the following dynamic problem:

$$V(\omega_0) = \max_{p_{0,EC},p_{0,BC}} \mathbb{E}\Bigg[R(\omega_0) + \sum_{c_{1,BC},Q^H_{0,EC},Q^L_{0,EC}} \mathbb{P}(c_{1,BC}, Q^H_{0,EC}, Q^L_{0,EC}|\omega_0, p_{0,EC}, p_{0,BC})\mathbb{E}[V(\omega_1)]\Bigg] \tag{6}$$

where ω_0 represents the information available to the airline at the beginning of period *0*. In particular, $\omega_0 = [c_{BC}, c_{EC}, \Psi_0]$, where c_{BC}, c_{EC} denote the total number of seats in Business and Economy Class, respectively, and Ψ_0 is the demand shock in $t = 0$. The term $\mathbb{E}[R(\omega_0)]$ represents the expected[6] revenues generated by $t = 0$ retail sales:

$$\mathbb{E}[R(\omega_0)] = \mathbb{E}\Bigg[p_{0,EC}\tilde{Q}_{0,EC} + p_{0,BC}\tilde{Q}_{0,BC}\Bigg]$$

with $\tilde{Q}_{0,EC} = \min\{Q_{0,EC}, c_{0,EC}\}$ and $\tilde{Q}_{0,BC} = \min\{Q_{0,BC}, c_{0,BC}\}$, where $Q_{0,k}$ is the real-

[6] The expectation is taken with respect to the number of customers randomly arriving to the market of airline tickets and the mixture of types.

ized number of sales in cabin k that cannot exceed its corresponding residual capacity, $c_{0,k}$. The term $\mathbb{P}(c_{1,BC}, Q^H_{0,EC}, Q^L_{0,EC}|\omega_0, p_{0,EC}, p_{0,BC})$ represents the state transition probability, where $Q^H_{0,EC}$ and $Q^L_{0,EC}$ are the realized Economy Class sales to H- and L-types[7], and $\mathbb{E}[V(\omega_1)]$ represents the expected value function in $t = 1$ with state space ω_1. In $t = 1$, the information relevant for the firm is $\omega_1 = [c_{1,BC}, Q^H_{0,EC}, Q^L_{0,EC}, \Psi_1, \Psi_0, p_{0,EC}, p_{0,BC}]$. This information set includes the left capacity in both Economy ($c_{1,EC}$) and Business Class ($c_{1,BC}$), the $t = 1$ demand shock (Ψ_1), the $t = 0$ demand shock (Ψ_0), the prices set in period $t = 0$ ($p_{0,EC}$ and $p_{0,BC}$) and the realized type-specific sales in Economy Class ($Q^H_{0,EC}, Q^L_{0,EC}$). The reason why, when setting prices at the beginning of period $t = 1$, the firm takes into account Ψ_0, the prices in period $t = 0$ ($p_{0,EC}$ and $p_{0,BC}$), $Q^H_{0,EC}$, and $Q^L_{0,EC}$ is that the number of customers choosing to upgrade is influenced by these variables, as indicated by expression (4).

In the last period, $t = 1$, the airline offers tickets both retail and with upgrades by choosing $p_1 = [p_{1,EC}, p_{1,BC}, p_{UP}]$. The $t = 1$ value function is then:

$$V(\omega_1) = \max_{p_{1,EC}, p_{1,BC}, p_{UP}} \mathbb{E}[R(\omega_1)]. \tag{7}$$

In (7), the term $\mathbb{E}[R(\omega_1)]$ represents expected revenues from retail and upgrade sales:

$$\mathbb{E}[R(\omega_1)] = \mathbb{E}\Bigg[p_{1,EC}\tilde{Q}_{1,EC} + p_{1,BC}\tilde{Q}_{1,BC} + p_{UP}\tilde{Q}_{UP}\Bigg] \tag{8}$$

with $\tilde{Q}_{1,EC} = \min\{Q_{1,EC}, c_{1,EC}\}$ and $\tilde{Q}_{1,BC} = \min\{Q_{1,BC}, c_{1,BC}\}$, where $Q_{1,k}$ represents the realized number of sales in cabin k that cannot exceed its corresponding residual capacity, $c_{1,k}$[8]. Additionally, I define $\tilde{Q}_{UP}$ as:

$$\tilde{Q}_{UP} = \sum_{\tilde{c}_{BC}} Pr(\tilde{c}_{BC}|\omega_1) \min\{Q_{UP}(\omega_2), \tilde{c}_{BC}\} \tag{9}$$

[7] Recall that $c_{1,EC} = c_{0,EC} - Q^H_{0,EC} - Q^L_{0,EC}$ represents the number of empty seats at the beginning of $t = 1$. Therefore, information on $Q^H_{0,EC} + Q^L_{0,EC}$ is the same as $c_{1,EC}$.

[8] My model prevents the firm from overselling in any cabin in any t. In principle, I could relax this assumption for Economy Class: since the airline knows that some customers would upgrade, it could oversell Economy Class. In practice, I exclude this case for computational simplicity. This reduces the impact of upgrades on the overall firm's pricing strategy. Therefore, counterfactual results - assessing the value of the upgrade option - derived from my model can be considered a lower bound for the effect of upgrades.

with $\omega_2 = [\tilde{c}_{BC}, \Psi_0, p_{0,EC}, p_{0,BC}, p_{UP}, Q^H_{0,EC}, Q^L_{0,EC}]$, where $\tilde{c}_{BC}$ is the left capacity in Business Class after $t = 1$ retail sales, and $Q_{UP}(\omega_2)$ represents the number of upgrading customers.

As evident from expressions (7) and (9), in $t = 1$ the airline simultaneously chooses retail and upgrade prices. However, firstly the airline allocates retail purchases, then, if there are empty premium cabin seats, it allocates upgrades. This assumption reflects the airline practice of offering seats with upgrades and retail sales at the same time. However, by prioritizing retail sales, I do not consider the potential misallocation and consequent potential reduction in consumer surplus that may arise from sales to upgrading customers instead of higher value retail customers.

I make three assumptions that simplify the problem on the supply side. Firstly, the booking horizon includes two periods only. While increasing the number of periods would make the pricing problem more realistic, it would also significantly increase computational complexity. For example, let's consider a firm selling tickets retail over $t \in \{0, 1, ..., T\}$, with T being departure day and the upgrade sales period. Firm's information set in the last period T includes previously realized prices, previously realized demand shocks and type-specific Economy Class sales. Being the airline forward looking, information sets of all periods t include previously realized prices and demand shocks, along with expected future prices, demand shocks and expected future realizations of Economy Class retail sales. Evaluating expectations and optimal prices for any combination of variables in the state space is not feasible. Therefore, to keep the problem tractable, I consider only a two period problem. Secondly, I assume that all tickets within a class (Economy Class and Business Class) have the same quality. In reality, tickets within the same class may have varying levels of flexibility, refundability, or additional services and thus different prices. However, by assuming uniform quality within each class[9], I decrease the number of prices the airline needs to determine: this reduces the dimensionality of the model and its complexity. At the same time, it still allows me to analyze the main tradeoffs of the upgrade option. Lastly, stemming from the demand side, I impose that customers are not strategic. As discussed in Section 3, customers do not delay the purchase of a Business Class ticket in $t = 0$, in the hope of an upgrade in $t = 1$. Additionally, customers do not

[9] Lack of reliable data on tickets' flexibility or refundability, as described in Section 2.1, is another reason for this assumption.

time their purchase strategically. These two assumptions greatly simplify the dynamic pricing problem, since I do not need to consider customers' expectations when evaluating firm's optimal decisions. Furthermore, they remove any commitment issues on the part of the firm. Since customers are not strategic, the firm's ability to commit to certain pricing strategies becomes irrelevant.

The mechanics of the model described in expressions (6) and (7) are similar to those in Aryal et al. (2023) and in Williams (2022). In particular, Aryal et al. (2023) assumes that the distribution of type-specific preferences is constant over time, a parameter known to the firm since the initial period for each flight. Consequently, this assumption implies that intertemporal variation in arrival rates, the composition of customers types, and level of unsold capacity jointly drive intertemporal variation in prices within a flight. In my case, intertemporal variation in the demand shock, which then determines time-flight specific preferences, further contributes to intertemporal price variation at the flight level. With this slightly more general modeling assumption I can explain large within-flight intertemporal price variation, particularly noticeable for Business Class. On the other hand, this increases the complexity of my model's solution as the numerical approximation of $t = 1$ firm's revenues expectation becomes more demanding. As in Aryal et al. (2023), Williams (2022) models type-specific preferences to be constant over time and known by the firm since the beginning of the booking horizon, so that variation in arrival rate, mixture of type and level of unsold capacity drive intertemporal variation in prices. Additionally, Williams (2022) includes firm-specific idiosyncratic shocks, playing a similar role as demand shocks in Aryal et al. (2023) and in the model delineated in my paper. In particular, these elements explain within-time price variation across flights with the same levels of unsold capacity.

3.3 Supply side: trade-offs

The airline faces intertemporal and intratemporal tradeoffs. Given capacity constraints and given potentially higher demand shocks in $t = 1$ compared to $t = 0$, the airline needs to balance the benefits of an extra sale in $t = 0$ with lower, but potentially more profitable, expected sales in $t = 1$. At the same time, the airline sorts customers into two different cabins. These tradeoffs interact with the upgrade option. Given capacity constraints, the upgrade option modifies the opportunity cost of an increase in Business Class and Economy Class retail prices in both $t = 0$ and $t = 1$ and, ultimately, how the upgrade option affects the pricing problem depends on demand's estimates.

To see the complex relation between the upgrade option and the airline's pricing problem, I start from $t = 1$. The optimal prices $p_1 = [p_{1,EC}, p_{1,BC}, p_{UP}]$ needs to satisfy the following system of first order conditions:

$$\begin{cases} \dfrac{dV(\omega_1)}{dp_{1,EC}} = \mathbb{E}[\tilde{Q}_{1,EC}] + p_{1,EC}\frac{d\mathbb{E}[\tilde{Q}_{1,EC}]}{dp_{1,EC}} + p_{1,BC}\frac{d\mathbb{E}[\tilde{Q}_{1,BC}]}{dp_{1,EC}} + p_{UP}\frac{\mathbb{E}[\tilde{Q}_{UP}]}{dp_{1,EC}} = 0 \\ \dfrac{dV(\omega_1)}{dp_{1,BC}} = p_{1,EC}\underbrace{\dfrac{d\mathbb{E}[\tilde{Q}_{1,EC}]}{dp_{1,BC}}}_{(A')} + p_{1,BC}\underbrace{\dfrac{d\mathbb{E}[\tilde{Q}_{1,BC}]}{dp_{1,BC}}}_{(B')} + \mathbb{E}[\tilde{Q}_{1,BC}] + p_{UP}\underbrace{\dfrac{\mathbb{E}[\tilde{Q}_{UP}]}{dp_{1,BC}}}_{(C')} = 0 \\ \dfrac{dV(\omega_1)}{dp_{UP}} = \mathbb{E}[\tilde{Q}_{UP}] + p_{UP}\frac{\mathbb{E}[\tilde{Q}_{UP}]}{dp_{UP}} = 0 \end{cases} . \quad (10)$$

These conditions capture the intratemporal tradeoffs as well as the intertemporal dimension introduced by the upgrade option. For example, an increase in $p_{1,BC}$ has three effects. (A') It increases the expected quantity of Economy Class retail sales in $t = 1$, (B') it decreases the expected quantity of Business Class retail sales in $t = 1$, (C') it increases the probability of upgrading sales[10]. Effects (A') and (B') capture the intratemporal tradeoff, whereas (C') includes the intertemporal dimension of the problem.

The airline faces similar tradeoffs in $t = 0$, where the optimality of $p_0 = [p_{0,EC}, p_{0,BC}]$ requires:

$$\begin{cases} \dfrac{dV(\omega_0)}{dp_{0,EC}} = \mathbb{E}[\tilde{Q}_{0,EC}] + p_{0,EC}\frac{d\mathbb{E}[\tilde{Q}_{0,EC}]}{dp_{0,EC}} + p_{0,BC}\frac{d\mathbb{E}[\tilde{Q}_{0,BC}]}{dp_{0,EC}} + \frac{d\tilde{\mathbb{E}}[V(\omega_1)]}{dp_{0,EC}} = 0 \\ \dfrac{dV(\omega_0)}{dp_{0,BC}} = p_{0,EC}\underbrace{\dfrac{d\mathbb{E}[\tilde{Q}_{0,EC}]}{dp_{0,BC}}}_{(A)} + p_{0,BC}\underbrace{\dfrac{d\mathbb{E}[\tilde{Q}_{0,BC}]}{dp_{0,BC}}}_{(B)} + \mathbb{E}[\tilde{Q}_{0,BC}] + \underbrace{\dfrac{d\tilde{\mathbb{E}}[V(\omega_1)]}{dp_{0,BC}}}_{(C)} = 0 \end{cases} . \quad (11)$$

Let's consider an increase in $p_{0,BC}$ on $V(\omega_0)$: this has three effects. (A) It increases the expected quantity of Economy Class retail sales in $t = 0$, (B) it decreases the expected quantity of Business Class retail sales in $t = 0$, (C) it affects the future value of sales. Effects (A) and (B) capture the intratemporal tradeoff, whereas (C) captures the intertemporal dimension of the problem, which embeds the effects on retail sales and

[10] As $p_{1,BC}$ increases, because of (B'), the probability of empty seats in Business Class after retail sales increases, this leads to an increase in the probability of upgrade sales.

upgrades. In particular, an increase in $p_{0,BC}$ has three effects on $\tilde{\mathbb{E}}[V(\omega_1)]$[11]. (1) It affects the transition probability; (2) It increases the probability of an emptier Business Class at the end of $t = 1$, thus it affects the number of upgrading customers; (3) It increases the probability that an Economy Class ticket holder purchases an upgrade, via a change in the upgrade choice probability.

4 Econometric model, estimation and identification

In this section, I first outline the main parametric assumptions of the structural model of Section 3. Secondly, I discuss its estimation and the identification argument.

4.1 Econometric model

I describe the econometric model in two steps. Firstly, I examine its parametrization at the aircraft-level, then, I discuss the assumptions for its estimation at the route-level via random coefficients.

In order to identify and estimate the primitives of the structural model, I impose simplifying parametric restrictions. Recall that the vector $\Psi = \left(\left\{\{F_v^{kt}(\cdot), F_\xi^{kt}(\cdot), \alpha_k\}_{k\in\{H,L\}}, \lambda_t, \theta_t\right\}_{t\in\{0,1\}}\right)$, as defined in Section 3.1, represents the time-specific primitives of the model, which includes type-specific preferences, parameters describing arriving customers and inattention parameters. As a first step, I impose parametric assumptions on consumers' preferences: I assume that $v_{kt} \sim Exp(\beta_{kt})$ and $\xi_{kt} \sim Unif(1, \gamma_{kt})$. With these restrictions, I fully specify type-time-specific preferences with two parameters only: the mean β of the willingness to pay, v, and the upper bound γ of the value for comfort, ξ. As shown in Section 4.2, given the observables in the data, I can only identify up to two parameters per consumer type-period of the booking horizon. Model's primitives at the flight-level are given by:

$$\Psi = \left(\beta_{H0}, \beta_{H1}, \beta_{L0}, \beta_{L1}, \xi_{H0}, \xi_{H1}, \xi_{L0}, \xi_{L1}, \lambda_0, \lambda_1, \theta_0, \theta_1, \alpha_H, \alpha_L\right) \in \mathbb{R}^{14}.$$

Rather than estimating Ψ at the flight-level, I impose a random coefficients structure to estimate its distribution at the route-level, similarly as in Aryal et al. (2023). I assume that β_{kt} and γ_{kt} are identically and independently distributed across flights on the same

[11] See the Appendix A.3 for the decomposition of the derivative.

route, time and types according to $TN(\mu_{kt}, \sigma_{kt})$[12] and $Uniform(1, \kappa_{kt})$, respectively. On the other hand, I impose λ_t and θ_t to be constant at the route-level. This implies that each route is characterized by the following set of coefficients:

$$\Theta = \left(\left\{ \{\mu_{kt}, \sigma_{kt}, \kappa_{kt}, \alpha_k\}_{k\in\{H,L\}}, \lambda_t, \theta_t \right\}_{t\in\{0,1\}} \right) \in \mathbb{R}^{18}. \tag{12}$$

Therefore, rather than estimating Ψ for any observed flight within a route, I estimate its distribution at the route-level: this reduces the number of estimable parameters to 18. Despite these parametric restrictions being more restrictive than a fully nonparametric random coefficient model at the route-level, they still allow me to reproduce heterogeneity in demand while matching empirical and simulated moments.

4.2 Identification

In this section, I present the identification of the random coefficient model described in Section 4.1, by starting from the identification of Ψ at the flight-level. The argument leverages both demand and supply side restrictions, as in Aryal et al. (2023) and Williams (2022).

For a specific flight, given the observed retail prices and retail sales in any period t[13], I can identify the demand shocks for both types, the arrival rate and the share of H-types. Then the share of upgrading customers allows me to identify inattention parameters for both types. For example, let's start from *t=0*. I derive the distributions of retail sales

[12] Truncated at 0 normal distribution.

[13] Each flight in the data is represented by a set of prices $p = [p_{0,EC}, p_{0,BC}, p_{1,EC}, p_{1,BC}, p_{UP}]$ and observed type-specific sales.

and upgrades for both H-types and L-types, given $\psi \in \Psi$:

$$\begin{aligned}
Q^{H,0,EC}(p;\psi) &\sim Po\Big(\lambda_0\theta_0 s_{H,EC}\big(p;\beta_{H0},\gamma_{H0}\big)\Big)\\
Q^{H,0,BC}(p;\psi) &\sim Po\Big(\lambda_0\theta_0 s_{H,BC}\big(p;\beta_{H0},\gamma_{H0}\big)\Big)\\
Q^{L,0,EC}(p;\psi) &\sim Po\Big(\lambda_0(1-\theta_0) s_{L,EC}\big(p;\beta_{L0},\gamma_{L0}\big)\Big)\\
Q^{L,0,BC}(p;\psi) &\sim Po\Big(\lambda_0(1-\theta_0) s_{L,BC}\big(p;\beta_{L0},\gamma_{L0}\big)\Big)\\
Q^{H,0,UP}(p;\psi) &\sim Bin\Big(Bin(\bar{Q}_{H,0,EC},\alpha_H); s_{UP}\big(p;\beta_{H0},\gamma_{H0}\big)\Big)\\
Q^{L,0,UP}(p;\psi) &\sim Bin\Big(Bin(\bar{Q}_{H,0,EC},\alpha_L); s_{UP}\big(p;\beta_{L0},\gamma_{L0}\big)\Big)
\end{aligned} \tag{13}$$

where $\bar{Q}_{H,0,EC}$ and $\bar{Q}_{L,0,EC}$ are the realized number of sold tickets in period 0 by H-types and L-types respectively. Intuitively, for any flight, there are two sets of independent restrictions. There are 10 restrictions from the demand side: system (13) describes $t = 0$ demand restrictions, but, then, there are also 4 restrictions from $t = 1$ retail sales. Furthermore, there are 5 restrictions from the supply side, derived from the optimality of prices. This implies a system of 15 independent restrictions for a total of 14 parameters.

Based on the previous argument, I argue identification of demand shocks at the flight-level. This implies that identification of their non-parametric distribution at the route-level is feasible. It follows, then, that I can identify shocks' distribution under parametric assumptions as well. In this section, I provide an intuitive explanation of the moments used to identify the parametric random coefficient model. The identifying moments are:

(i) distribution of realized prices for $j \in \{EC, BC\}$ and $t \in \{0,1\}$;

(ii) average of retail sales for $j \in \{EC, BC\}$, $t \in \{0,1\}$ and $k \in \{H, L\}$;

(iii) average fraction of Business Class retail sales over all sales in any period $t \in \{0,1\}$ for any type $k \in \{H, L\}$;

(iv) average number of upgrades for $k \in \{H, L\}$.

The mean of the realized price, along with their distribution, provides information about the mean, μ, and the variance, σ, of the WTP. If customers' WTP is highly volatile, optimally-set prices display high variance. Similarly, if the average WTP is high, the airline charges higher prices on average. The ratio between total sales of H-types and L-types is informative for customers' mixture, θ. Large L-type sales' share indicates a large share of arriving L-types customers. When considering a specific type, the ratio of Business Class retail sales to Economy Class sales is informative for the value for comfort, κ. Given some prices, a large proportion of Business Class purchases indicate a large value comfort. Being preferences identified, the average number of sales provides insight into the arrival rate, λ: if more shoppers enter the market, more sales take place. Finally, the share of upgrading customers describes the average number of attentive travelers within each type. In Appendix A.4, I provide an identification proof for demand shocks at the flight-level, then I argue identification at the route-level, within a simplified random coefficient model.

4.3 Estimation

In this section, I discuss how I estimate the model. In the first part, I present the simulated method of moments (SMM) estimator. In the second part, I discuss parameters' estimates and model fit.

I describe the SMM procedure in two steps: firstly, I outline the evaluation of the empirical moments, then of their simulated counterpart. The approach is in line with Aryal et al. (2023) and Nevo et al. (2016). I define the optimal estimator $\hat{\theta}$ for $\theta \in \Theta$ as the solution of the following problem:

$$\arg\min_{\theta} L(\theta) = \arg\min_{\theta} \left(m^{data} - m(\theta) \right)' \left(m^{data} - m(\theta) \right) \tag{14}$$

where $m^{data} - m(\theta)$ is a 1xM vector, which is the difference between observed moments, m^{data}, and the corresponding simulated one, $m(\theta)$, with M being the number of moments. In particular, I obtain $\hat{\theta}$ by minimizing $L(\theta)$ over 100,000 different values of θ. Solving problem (14) requires the evaluation of both m^{data} and $m(\theta)$. I compute m^{data} from the original dataset in two steps. Firstly, I aggregate initial purchase dates (in terms of their distance from the departure day) into two periods: *t=0* includes all days of the booking horizon except for the last two, which, in turn, constitute $t = 1$. At the same time, as in

Aryal et al. (2023), I assume that the type k is observable from the reason for traveling[14]. Then, for all flights I compute the total number of sales for any type and average prices in any period. The second element needed to solve problem (14) is $m(\theta)$, which requires solving the decision problem of the firm. Firstly, for $N^s(= 100)$ different draws of Ψ from the same θ, I solve the airline's pricing problem defined by expressions (6) and (7), then I evaluate the simulated moments $m(\theta)$. Being pricing decisions dependent on c_{EC} and c_{BC}, I solve the pricing problem of the airline separately for various combinations of total capacities observed in the data. Lastly, I evaluate estimates and bootstrap standard errors, by resampling 100 times at the flight-level.

Before describing parameters' estimates, I discuss three procedural assumptions employed for estimation. Firstly, I estimate preferences at the aircraft-route-level. Estimation at the aircraft-level is due to the dependence of optimal simulated prices on initial levels of capacity. Therefore demand estimates reflect aircraft-specific tastes. Estimation at the route-level implies two different sets of estimates given the available data: one for the domestic and one for the international route. Moreover, estimation at the route-level is consistent with practices in the industry (IATA). The second assumption is considering, when it is available, Premium Economy Class part of Business Class. A firm setting optimal prices for two products, rather than three, simplifies the pricing problem and eases the simulation of the model. The third assumption is to impose $\mu_{H0} = \mu_{H1}$, $\sigma_{H0} = \sigma_{H1}$ and $\mu_{L0} = \mu_{L1}$. This partially reduces the flexibility of the model, but simplifies the minimization problem (14), as it reduces the search over 15 parameters only, rather than over 18. This simplification still allows me to match the data generally well.

Table 4 and 5 show estimation results for the largest aircraft in the data flying over the international route[15][16]. The mean willingness to pay for an Economy ticket on a flight over the international route is 306$ for H-types and 220$ for L-types. On average, there is a 40% difference in willingness between types. As a benchmark in the literature, Aryal

[14] I consider travelers reporting business as their reason for traveling as H-types, the others as L-types.

[15] There are 294 flights of this kind. I estimate the model for those flights displaying $p_{EC,0} \in [200, 400]$, $p_{EC,1} \in [200, 650]$, $p_{BC,0} \in [200, 650]$ and $p_{BC,1} \in [700, 3000]$. I consider only flights displaying all these four prices, for a total number of 104 flights. I select the sample in this way in order to eliminate outliers, and reduce the size of the price grid over which the airline makes its optimal pricing decision, in order to increase the speed of the simulation.

[16] This particular aircraft has capacities of 247 for Economy Class, 21 for Premium Economy, and 31 for Business Class. I set the capacities to $c_{EC} = 247$ and $c_{BC} = 51$ in the simulation, as Business Class includes Premium Economy Class seats. In Appendix A.9.2, I show estimation results for the smallest aircraft in the data as well. At the beginning of Section A.9, I describe the main aircraft in the data.

et al. (2023) find a 20% percentage difference between types. However, the difference in the value for comfort per flight across types is not as large, in $t = 0$ H-types value comfort 3% more than L-types, whereas in $t = 1$ H-types value comfort 15% more than L-types. In terms of the value placed on Business Class compared to Economy Class, my estimates suggest that the two types value Business Class, on average, twice as much as Economy Class. In comparison to the estimates of the value for comfort in Aryal et al. (2023), where travelers value the comfort of the premium product on average 50% more than the regular product, my findings indicate a larger taste for quality. This is likely due to the larger average premium cabin retail prices observed in my data.

The average number of customers shopping for a ticket in $t=0$ is 488, whereas in $t = 1$ is 50. The stark decrease is consistent with how I divided the booking horizon, as $t = 0$ includes the large majority of days before departure. On the other hand, the fraction of customers traveling for business purposes slightly increases over time. This finding is consistent with Aryal et al. (2023) and Williams (2022). Regarding the inattention parameters, which measure the fraction of Economy Class ticket holders who open the email sent by the airline containing the notification on the upgrade possibility, they are 0.15 and 0.09 for H-types and L-types. As a benchmark, travel industry surveys report that between 20% and 40% of people receiving a travel-related email open it[17].

4.4 Goodness of fit: discussion

In this section, firstly, I discuss the model's ability to fit the data for large aircraft flying over the international route. Secondly, as an illustration of robustness, I describe the relevance of inattention parameters for fitting purposes.

Overall, the model approximates the data well for prices and sales along both the retail and upgrades channel. Figures 4, 5 and 6 show how simulated prices and sales fit the observed data along the retail and upgrade channel. In Figures 4 and 5 the blue line represents the mean observed in the data, whereas the blue shaded area represents the central 80% of the distribution. The red line represents the average across all the bootstrap estimates, while the red shaded area represents the central 80% of the simulated distribution. In particular, the lowerbound (upperbound) is the mean bootstrap estimate

[17] See: ConstantContact and CampaignMonitor.

of the 10th (90th) percentile of the distribution. Figure 6 displays model's prediction for upgrade prices and sales. The blue line represents the distribution observed in the data, whereas the orange line represents the average distribution across bootstrap estimates. Model's fitted values are generally accurate for both retail and upgrade channel, with a few exceptions. In particular, in the last period my model predicts simulated prices that are lower than the observed ones for Business Class. The assumption, which ensures computational tractability, of constant willingness to pay over time likely explains the result. As a robustness check of the model's fitting ability, I estimate it for small aircraft flying over the domestic route[18], and I show its fit in Appendix A.9.2. Despite differences in patterns in the observed data with respect to the large aircraft flying over the international route, the estimated model fits the data well, especially for retail prices and sales.

With respect to the empirical airline demand models described in Aryal et al. (2023) and Williams (2022), my framework includes inattention coefficients (α_H and α_L). These parameters play a crucial role in fitting the relevant moments in the data, in particular those related to upgrades sales. Appendix A.8 shows the importance of inattention coefficients, by considering estimates and fit of a model with fully attentive customers ($\alpha_H = \alpha_L = 1$). Visually, a model with fully attentive customers fits the data worse than a model with inattentive travelers, in particular for upgrade sales. In fact, when all customers pay attention to the airline's notification related to the upgrade option, the estimated model predicts a too large number of upgrading customers[19].

5 Counterfactual

In this section, I describe how the upgrade option affects airline pricing decisions and welfare. In Section 5.1, I describe the role of the upgrade option as a sequential price discrimination tool and its role in managing limited inventory. In Section 5.2, firstly, I analyze the aggregate welfare consequences arising from the introduction of upgrades.

[18] The most popular flight over the domestic route does not have Premium Economy, and it displays $c_{EC} = 153$ and $c_{BC} = 16$.

[19] Considering inattentive customers has consequences on counterfactual results. In particular, travelers being fully attentive implies that the introduction of the upgrade option generates larger pricing distortions with respect to the case of inattentive travelers. In Appendix A.5, I explore the role of upgrades as a sequential price discrimination tool, and I compare the case where travelers are inattentive with one where travelers are fully attentive. Pricing distortions are larger with inattentive travelers.

Afterwards, I focus on the distributional welfare effects of upgrades between travelers and the firm.

5.1 The economics of upgrades and the role of demand shocks

To understand how upgrades work, I compare airline's pricing decisions with and without upgrades under scenarios with and without capacity constraints. On one hand, the difference in prices between the scenario with and the scenario without upgrades, in the absence of capacity constraints, illustrates the role of upgrades as a sequential price discrimination tool. On the other hand, comparing these differences with those observed when the airline faces capacity constraints shows how the airline uses upgrades as a way to manage inventory. In this section, I first discuss how these two channels work on average across all flights, and then I discuss how these two channels work differently conditional on the demand shock.

Table 6 shows how the upgrade option affects on average the airline's pricing problem with and without capacity constraints. In the absence of capacity constraints, there exists no connection between the retail pricing decisions in the two periods, and the upgrade option only influences prices in $t = 0$. Specifically, when setting prices in $t = 0$, the airline anticipates that some Economy Class ticket holders may choose to upgrade to Business Class if given the possibility of accessing it at a reduced price. Introducing the upgrade option, then, leads to two effects. On one hand, the average opportunity cost of decreasing Economy Class ticket prices diminishes: lower prices for Economy Class incentivize more customers to purchase it, thus increasing the number of potentially upgrading travelers. Introducing upgrades results in a 1.3% average decrease in Economy Class prices. On the other hand, the average opportunity cost of increasing Business Class ticket prices decreases since customers who did not purchase Business Class retail initially can still upgrade in $t = 1$. The introduction of upgrades leads to an average increase of 1.6% in Business Class prices.

Table 6 also shows how capacity constraints (with total capacity in Economy Class set at $c_{EC} = 247$, and in Business Class set at $c_{BC} = 51$) affect airline's pricing decisions on average across flights, and how they interact with the upgrade option. When the firm introduces capacity constraints, the low demand for Economy Class and high demand for

Business Class relative to the constraints result in a slight change in prices for Economy Class and a significant increase in retail prices for Business Class due to scarcity. Moreover, compared to the case without constraints, the introduction of upgrades impacts both $t = 0$ and $t = 1$ prices. Sequential price discrimination affects $t = 0$ prices, whereas the interplay between upgrades and capacity constraints affects both $t = 0$ and $t = 1$ prices. On average, as shown in Figures 7 and 8, when the airline introduces the upgrade option, it further increases - with respect to the scenario without capacity constraints - Business Class prices in $t = 0$ in order to reduce the number of premium cabin sales and sellouts in the initial period and then allow for potentially higher value retail sales in $t = 1$. In this way the upgrade option works as an inventory management tool, leading to an average 3% increase in $t = 0$ Business Class prices. As a consequence, the introduction of the upgrade option reduces sales of Business Class in $t = 0$ more if there are constraints than if there are not. The airline compensates the loss in revenues from reduced Business Class sales by decreasing Economy Class prices in $t = 0$ slightly more (1.6%) if there are constraints, in order to induce more customers to access Economy Class and, then, potentially upgrade. Furthermore, when there are capacity constraints, the upgrade option induces price changes also in $t = 1$. Indeed, due to limited capacity in premium cabin, upgrading customers compete with retail customers for the same seats in Business Class. This enables the airline to increase Business Class retail price in $t = 1$. Moreover, due to upgrading customers leaving Economy Class emptier, the airline finds it optimal to decrease its $t = 1$ price to attract more passengers and fill the vacant seats[20].

The role of demand shocks

Whether the upgrade option, beyond working as a way to sequentially price discriminate, also serves as a tool to manage inventory depends on the size of $t = 0$ demand shocks. In case of low initial demand shocks, upgrades work mainly as a tool to sequentially price discriminate. Conversely, in case of a large demand shock, upgrades work as both a tool to sequentially price discriminate and to manage inventory. In the former case, upgrades reduce the *spoilage* issue of an empty Business Class, by allowing Economy Class ticket

[20] In Appendix A.10, I show the effects of the upgrade option with and without capacity constraints, considering also welfare. Counterfactual results indicate that the upgrade option increases consumer and producer surplus in both scenarios.

holders to fill premium cabin, whereas in the latter, upgrades reduce the *spillage* problem of early sellouts[21].

When the airline faces low initial demand shocks, the probability of selling out in either cabins is negligible. This implies that capacity constraints have little effects on the pricing problem of the airline, and, thus, the airline uses upgrades mainly to sequential price discriminate $t = 0$ travelers. As shown in Table 7, percentage changes in $t = 0$ prices induced by the introduction of the upgrade option are the same with and without constraints in case of low demand shocks. Because of low demand for tickets in $t = 0$, due to the low initial demand shock, the airline practically does not face capacity constraints in $t = 1$, therefore upgrades have negligible effects on $t = 1$ prices. The latter fact is shown in Table 8, where percentage changes induced by the upgrade option in $t = 1$ display high variance and are not statistically meaningful. In general, on unpopular flights, featured by low-demand shocks, upgrades work as a sequential price discrimination tool, and mitigate spoilage issues in premium cabin.

Conversely, in case of a large demand shock, the airline, beyond using the upgrade option to sequentially price discriminate $t = 0$ customers, also uses it to manage limited inventory. Specifically, in case of a large initial-period demand shock, the probability of Business Class selling out in $t = 0$ is large. In order to avoid the risk of selling it out and missing on high-value sales in the last period, the airline exploits the upgrade option to increase Business Class prices in $t = 0$. With respect to the situation without capacity constraints, the increase in $t = 0$ Business Class prices due to the introduction of the upgrade option is larger when there are capacity constraints, as shown in Table 7. This is due to upgrades being used as tool to manage inventory, rather than sequential price discriminate only. This large increase in premium cabin prices has two effects shown in Tables 9 and 10. On one hand, it reduces Business Class initial sales and sellouts, on the other hand, it increases Economy Class initial sales and sellouts, due to customers buying the regular product rather than the more expensive premium one in $t = 0$. This benefits the airline as the number of potentially upgrading travelers increases. Furthermore, in $t = 1$, upgrading customers compete with retail purchasers for the same Business Class

[21] Empty flights and early sellouts are widely recognized problems in the airline industry: "Hold inventory (high) for too long, and they could risk having a plane depart with empty seats (spoilage). The stakes are incredibly high - sell too much too early at a lower price, and airlines might sell out too early missing out on high yielding last-minute sales (spillage)." (Alaska Airlines).

seats. This induces the airline to increase $t = 1$ Business Class retail prices, as shown in Table 8. In case of a large demand shock, many Economy class ticket holders upgrade: with respect to the scenario without upgrades, this leads to more Business Class sellouts and fewer Economy Class sellouts at the end of $t = 1$ as shown in Table 10. In general, on popular flights, featured by high-demand shocks, upgrades, beyond serving as a sequential price discrimination tool, work as an inventory management tool and mitigate spoilage issues in premium cabin.

5.2 Welfare effects of the upgrade option

In this section, firstly, I describe how the introduction of the upgrade option affects total welfare, then I discuss how it affects travelers and the airline separately. To provide further context, in Appendix A.6, I present a comparison of the welfare gains of the upgrade option with the gains from dynamic pricing and a free upgrade policy.

Aggregate welfare effects The upgrade option increases surplus of both travelers and the airline, thereby increasing efficiency, as shown in Table 11. In particular, consumer surplus increases by an average of 1.5% per flight, proving that the welfare gains enjoyed by upgrading customers outweigh the consumer welfare losses arising from higher Business Class prices. On the firm's side, airline's surplus increases by 2% per flight, primarily due to the substantial revenues generated by upgrading fees. As a benchmark, Cui et al. (2019) found a 4% increase in revenues when an airline introduced add-on products[22].

Effects on consumers. The introduction of the upgrade option modifies the airline's pricing problem, and thus it affects how the same customer behaves in the scenarios with and without upgrades and how welfare is distributed among travelers. Tables 12 and 13 provide a summary of the changes in customers' decisions based on simulations of 500 flights. Table 14 illustrates how consumer welfare and its distribution across cabins change when the upgrade option is removed.

Table 12 shows how the upgrade option affects the allocation of passengers across

[22] Cui et al. (2019) studied an airline, which allowed Economy Class ticket holders to upgrade to Premium Economy. There is no retail channel for Premium Economy. Their framework misses the interaction between capacity constraints and the upgrade option for the premium product.

cabins. For instance, in the presence of the upgrade option 181,032 customers enter the market of airline tickets, but do not purchase any tickets. However, when the upgrade option is eliminated, and different prices come into play, 861 of these customers switch to Economy Class, and 52 switch to Business Class. Table 12 aligns with Table 11, showing that the upgrade option reduces Business Class retail sales and increases Economy Class retail sales. Despite this, the number of passengers flying in Business Class is higher with the upgrade option, due to the 3,568 upgrading travelers. Furthermore, the upgrade option allows more travelers to fly. Table 13 presents the changes in consumers' behavior in percentage terms. It indicates the percentage of customers who change their decisions when the upgrade option is eliminated. In particular, 99.5% of customers who do not buy any ticket when there are upgrades continue to prefer the outside option even without upgrades. However, 0.5% of them switch to Economy Class in the absence of the upgrade option. According to Table 12 and 13, 2.5% of customers (88 in total) who upgrade to Business Class switch to a Business Class retail purchase when the upgrade option is not available. This demonstrates the "cannibalization effect" induced by upgrades, as the introduction of the upgrade option eliminates parts of Business Class retail sales.

Table 14 illustrates how consumer welfare and its distribution across cabins changes when the upgrade option is removed. Simulation results indicate that, on average, customers gain 1,227$ (+1.5%) per flight from the upgrade option. The upgrade option primarily benefits those customers in Economy Class with relatively high WTP and value for comfort, who are able to upgrade to Business Class. When the upgrade option is eliminated, two distinct segments of customers emerge from this group. The first segment consists of customers with relatively lower WTP and value for comfort, who end up flying in Economy Class. The second segment comprises customers with relatively higher WTP and value for comfort, who immediately purchase Business Class tickets at retail prices. Both segments enjoy the benefits of the upgrade option, as they gain access to the premium cabin at a discounted price. Furthermore, the upgrade option also benefits those customers with low WTP and low value for comfort who choose to purchase Economy Class tickets under both scenarios. These customers benefit from the upgrade option as it leads to lower prices in Economy Class. On the other hand, the upgrade option reduces the welfare of customers who choose to buy Business Class retail in both scenarios. These customers, with very high WTP and value for comfort, experience a loss in welfare due to the higher Business Class prices when the upgrade option is in place.

Effects on the firm The upgrade option modifies how the airline generates revenues between the two cabins, as shown in Table 15. Introducing upgrades increases revenues from the retail sales of Economy Class, but starkly decrease revenues from the retail sales of Business Class. These effects are attributed to lower prices in Economy Class, resulting in higher sales, and to higher prices in Business Class, leading to cannibalization of retail sales. However, the net effect of the upgrade option on revenues is positive. Table 16 presents the changes in the distribution of revenues across products resulting from the introduction of the upgrade option. Consistently with previous evidence and the original data in Table 1, up to 2.4% of total revenues are derived from upgrade fees.

6 Conclusion

This paper investigates the welfare implications of introducing upgrades within the airline industry. To achieve this, I analyze proprietary data from an international airline, that employs upgrades to allocate premium cabin seats. The data shows how the airline uses upgrades and allows me to estimate a structural model. The empirical analysis shows that upgrades are a relevant sales channel for premium products and that the airline employs them for price discrimination and inventory management purposes. After estimating a structural model, which captures key aspects of airline pricing decisions, including multiproduct offering, dynamic pricing, and capacity constraints, I quantify the effect of upgrades on welfare through counterfactual simulations. Results indicate that, on average, both consumers and the firm benefit from the upgrade option.

There are many interesting avenues for future research based on the findings presented in this paper. One natural direction is to explore the interaction between upgrade mechanisms and competition. While my analysis focuses on a monopolistic seller implementing upgrades, it would be valuable to examine the effect of upgrade mechanisms in competitive settings. Upgrades might soften competition among firms and increase market power, with potentially negative consequences for customers. Additionally, considering the impact of strategic customer behavior would be insightful. Strategic customers may time their initial purchase decisions[23] or delay the purchase of premium products to take advantage of future upgrade discounts. Although these strategic dimensions are not included in the current analysis for computational tractability, they might influence how the upgrade option affects welfare.

[23] As in Lazarev (2013).

Tables

Table 1: Distribution of transactions and revenues across products and sales channels

	Economy	Premium Economy	Business
Transactions	239,771	6,986	21,278
Retail	239,771 (100%)	5,542 (71%)	19,030 (90%)
Upgrades		2,278 (29%)	2,248 (10%)
Revenues (000)	66,490$	4,653$	23,437$
Retail (000)	66,490$ (100%)	3,841$ (83%)	22,365$ (95%)
Upgrades (000)		811$ (17%)	1,075$ (5%)

Notes: Revenues are expressed in thousands $. Percentages are with respect to total transactions (or revenues) of the corresponding class. When considering upgrades, I included also auction upgrades.

Table 2: Business Class, evidence of discount

Variable	Estimate
Average retail price (no upgrade)	1,337.98***
	(8.82)
Savings due to upgrades	-171.98***
	(13.46)
Number of transactions	17,413

Notes: Results are in $ and computed using sales of Business Class seats. When considering final price paid after upgrades, I included also auction upgrades. I dropped sales to customers with flyers-ID. Standard Errors are in parenthesis: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the flight-level.

Table 3: Premium Economy Class, evidence of discount

Variable	Estimate
Average retail price (no upgrades)	701.78***
	(6.88)
Savings due to Upgrade	-128.93***
	(4.55)
Number of transactions	7,455

Notes: Results are in $ and computed using sales of Premium Economy Class seats. I dropped sales to customers with flyers-ID and sales with auction upgrade. Standard Errors are in parenthesis: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard Errors are clustered at the flight-level.

Table 4: Preferences - large aircraft over the international route

t=0		t=1	
Parameter	Estimate	Parameter	*Estimate*
(μ_{H0}, σ_{H0})	(306.8,95.6)	(μ_{H1}, σ_{H1})	(306.8,95.6)
	((1.99),(4.97))		((1.99),(4.97))
κ_{H0}	3.3	κ_{H1}	3.7
	(0.0)		(0.0)
(μ_{L0}, σ_{L0})	(220.4,230.0)	(μ_{L1}, σ_{L1})	(220.4,300.0)
	((21.86),(0.0))		((21.86),(0.0))
κ_{L0}	3.22	κ_{L1}	3.2
	(0.01)		(0.02)

Notes: Bootstrap estimates and standard errors for flights in the international route on large aircraft (with $c_{EC} = 247$ and $c_{BC} = 51$). The data used for estimation includes 98 flights. I use 100 bootstrap samples, by resampling at the flight-level.

Table 5: Arrival process and inattention - large aircraft over the international route

Parameter	Estimate
λ_0	488
	(0.0)
λ_1	50
	(0.0)
θ_0	0.1
	(0.0)
θ_1	0.2
	(0.01)
α_H	0.15
	(0.01)
α_L	0.09
	(0.01)

Notes: Bootstrap estimates and standard errors for flights in the international route on large aircraft (with $c_{EC} = 247$ and $c_{BC} = 51$). The data used for estimation includes 98 flights. I use 100 bootstrap samples, by resampling at the flight-level.

Table 6: Counterfactual in levels, role of capacity constraints

	WITH capacity constraints		WITHOUT capacity constraints	
	With upgrades	Without upgrades	With upgrades	Without upgrades
	(1)	(2)	(3)	(4)
$p_{EC,0}$	303	308	313	317
	(3.33)	(2.95)	(2.95)	(2.49)
$p_{EC,1}$	418	422	430	430
	(5.29)	(5.64)	(5.28)	(5.28)
$p_{BC,0}$	1,305	1,268	1,152	1,134
	(12.77)	(11.32)	(14.23)	(11.96)
$p_{BC,1}$	996	983	848	848
	(13.92)	(24.15)	(15.61)	(15.61)
p_{UP}	297		268	
	(134)		(115)	
$passengers_{EC}$	164.5	167.2	145.69	150.27
	(2.85)	(3.24)	(2.25)	(2.82)
$passengers_{BC}$	29.3	23.82	42.36	35.13
	(0.86)	(0.83)	(1.73)	(1.61)
$upgrades$	7.11		7.78	
	(0.19)		(0.25)	

Notes: I evaluated the estimates and bootstrap standard errors for large aircraft over the international route. I used 10 bootstrap samples, each simulating 500 aircraft. The scenario with capacity constraints considers $c_{EC} = 247$ and in Business Class is $c_{BC} = 51$. The variable $passengers_k$ indicates the number of passengers flying in cabin k. The variable $sellouts_k$ indicates the fraction of flights (over the 500 simulated flights) that sellout in cabin k.

Table 7: Price change, sequential price discrimination and inventory management

Demand shock	Overall change $\Delta p_{0,EC}$	Overall change $\Delta p_{0,BC}$	Change due to SPD $\Delta p_{0,EC}$	Change due to SPD $\Delta p_{0,BC}$
H,H	-0.002	0.042	0.005	0.023
	(0.012)	(0.015)	(0.006)	(0.011)
H,M	0.004	0.035	-0.003	0.001
	(0.007)	(0.008)	(0.002)	(0.003)
M,H	-0.032	0.034	-0.034	0.000
	(0.015)	(0.008)	(0.015)	(0.001)
H,L	0.000	0.005	0.001	0.002
	(0.000)	(0.008)	(0.002)	(0.003)
L,H	-0.106	0.084	-0.106	0.084
	(0.029)	(0.041)	(0.002)	(0.041)
M,M	-0.009	0.031	-0.010	0.013
	(0.003)	(0.008)	(0.004)	(0.006)
M,L	-0.005	0.038	-0.011	0.036
	(0.005)	(0.016)	(0.005)	(0.018)
L,M	-0.005	0.028	-0.005	0.028
	(0.011)	(0.013)	(0.011)	(0.013)
L,L	0.016	0.012	0.016	0.012
	(0.017)	(0.012)	(0.017)	(0.012)

Notes: I simulated 500 flights operating in the international route, and I reported the percentage change induced by the introduction of the upgrade option. The overall change considers the percentage difference in $t = 0$ prices arising from the introduction of the upgrade option when the airline faces capacity constraints, thus $\Delta p = \frac{p^u - p^{NOu}}{p^{NOu}}$, where p^u is the price when the upgrade option is available, whereas p^{NOu} is the price when the upgrade option is not available. Columns under "change due to SPD" indicate the percentage change due to the introduction of the upgrade option when the airline does not face capacity constraints, and, thus, associated to the use of upgrades as a sequential price discrimination (SPD) tool. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. Bootstrapped standard errors over 10 samples are recorded.

Table 8: Leisure type demand shock and the effect of introducing upgrades on prices

Demand shock	Change in $p_{1,EC}$	Demand shock	Change in $p_{1,BC}$
H,H	0.016	H,H	0.145
	(0.061)		(0.138)
H,M	0.016	H,M	0.114
	(0.016)		(0.060)
M,H	0.011	M,H	0.096
	(0.025)		(0.041)
H,L	0.007	H,L	0.015
	(0.033)		(0.042)
L,H	-0.008	L,H	0.049
	(0.052)		(0.063)
M,M	0.004	M,M	0.064
	(0.012)		(0.024)
M,L	0.023	M,L	0.025
	(0.019)		(0.030)
L,M	-0.007	L,M	0.035
	(0.015)		(0.036)
L,L	0.005	L,L	0.061
	(0.046)		(0.069)

Notes: I simulated 500 flights operating in the international route under the two scenarios: with and without upgrades. In both cases, the airline faces the same demand shocks and capacity constraints. I evaluate optimal prices for any flight under the two scenarios and then consider their relative difference, in particular the *Change in* $p = \frac{p^U - p^{NoU}}{p^{NoU}}$, with p^U being the scenario with upgrades and p^{NoU} being the scenario without upgrades. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. Bootstrapped standard errors over 10 samples are recorded.

Table 9: Leisure type demand shock and the effect of introducing upgrades on retail sales

Demand Shock	Change in $q_{0,EC}$	Demand Shock	Change in $q_{0,BC}$
H,H	5.082	H,H	-3.258
	(2.669)		(1.276)
H,M	2.821	H,M	-2.705
	(0.958)		(0.570)
M,H	10.771	M,H	-3.653
	(2.674)		(0.314)
H,L	0.000	H,L	-0.008
	(0.000)		(0.026)
L,H	22.547	L,H	-1.956
	(6.877)		(0.783)
M,M	3.447	M,M	-1.250
	(1.151)		(0.229)
M,L	1.704	M,L	-0.271
	(1.194)		(0.079)
L,M	1.482	L,M	-0.267
	(1.805)		(0.143)
L,L	-1.093	L,L	-0.052
	(1.441)		(0.074)

Demand Shock	Change in $q_{1,EC}$	Demand Shock	Change in $q_{1,BC}$
H,H	0.415	H,H	-0.638
	(0.828)		(0.353)
H,M	0.108	H,M	-0.263
	(0.423)		(0.252)
M,H	0.257	M,H	-0.275
	(0.374)		(0.287)
H,L	0.038	H,L	-0.017
	(0.355)		(0.242)
L,H	0.252	L,H	-0.120
	(0.652)		(0.517)
M,M	0.373	M,M	-0.224
	(0.223)		(0.155)
M,L	-0.127	M,L	0.006
	(0.289)		(0.130)
L,M	0.363	L,M	-0.071
	(0.325)		(0.202)
L,L	0.093	L,L	-0.189
	(0.350)		(0.193)

Notes: I simulated 500 flights operating in the international route under the two scenarios: with and without upgrades. In any scenarios, the airline faces the same demand shocks. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. I evaluate retail sales for any flight under the two scenarios and then consider their difference, in particular *Change in* $q = q^U - q^{NoU}$. Bootstrapped standard errors over 10 samples are recorded.

Table 10: Leisure type demand shock and the effect of introducing upgrades on sellouts

Demand Shock	Change in $sellout_{0,EC}$
H,H	0.02870 (0.05563)
H,M	0.01446 (0.00965)
M,H	0.00000 (0.00000)
H,L	0.00000 (0.00000)
L,H	0.00000 (0.00000)
M,M	0.00000 (0.00000)
M,L	0.00378 (0.00613)
L,M	0.00000 (0.00000)
L,L	0.00000 (0.00000)

Demand Shock	Change in $sellout_{0,BC}$
H,H	-0.17494 (0.06752)
H,M	-0.07696 (0.03174)
M,H	-0.09009 (0.03779)
H,L	0.00000 (0.00000)
L,H	0.00000 (0.00000)
M,M	-0.01770 (0.00620)
M,L	0.00000 (0.00000)
L,M	0.00000 (0.00000)
L,L	0.00000 (0.00000)

Demand Shock	Change in $sellout_{1,EC}$
H,H	-0.00305 (0.05567)
H,M	-0.04342 (0.03066)
M,H	0.00000 (0.00000)
H,L	-0.30982 (0.07834)
L,H	0.00000 (0.00000)
M,M	-0.00394 (0.00398)
M,L	-0.01508 (0.01322)
L,M	0.00000 (0.00000)
L,L	0.00000 (0.00000)

Demand Shock	Change in $sellout_{1,BC}$
H,H	0.25012 (0.13784)
H,M	0.18193 (0.04648)
M,H	0.16662 (0.05424)
H,L	0.00417 (0.01318)
L,H	0.00000 (0.00000)
M,M	0.05332 (0.01599)
M,L	0.00000 (0.00000)
L,M	0.00000 (0.00000)
L,L	0.00000 (0.00000)

Notes: I simulated 500 flights operating in the international route under the two scenarios: with and without upgrades. In any scenarios, the airline faces the same demand shocks. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realizaiton of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. I evaluate the fraction (over the 500 simulations) of flights that sellout; in particular $\textit{Change in sellout}_k = sellout_k^U - sellout_k^{NoU}$, with $sellout_k^U$ being the fraction of flights which sellouts in cabin k in the scenario with the upgrade option, and $sellout_k^{NoU}$ being the fraction of flights which sellout in cabin k in the scenario without the upgrade option. Bootstrapped standard errors over 10 samples are recorded.

Table 11: Counterfactual in levels, introducing the upgrade option

	With Upgrades	Without upgrades	$\Delta = With - Without$ upgrades
$p_{EC,0}$	303	308	-5
	(3.33)	(2.95)	(1.05)
$p_{EC,1}$	418	422	-4
	(5.29)	(5.64)	(2.57)
$p_{BC,0}$	1305	1268	37
	(12.77)	(11.32)	(3.94)
$p_{BC,1}$	996	983	13
	(13.92)	(24.15)	(15.74)
p_{UP}	297		
	(134)		
$passengers_{EC}$	164.5	167.2	-2.698
	(2.85)	(3.24)	(0.51)
$passengers_{BC}$	29.3	23.82	5.478
	(0.86)	(0.83)	(0.21)
upgrades	7.11		
	(0.19)		
$sellout_{EC}$	0.01	0.03	-0.02
	(0.004)	(0.009)	(0.007)
$sellout_{BC}$	0.166	0.096	0.07
	(0.016)	(0.015)	(0.01)
CS	81,978	80,751	1,227
	(3,017)	(3,049)	(178)
PS	80,451	78,897	1,553
	(2,251)	(2,214)	(146)
TS	162,430	159,649	2,780
	(5,244)	(5,239)	(280)

Notes: I evaluated the estimates and bootstrap standard errors for large aircraft over the international route. I used 10 bootstrap samples, each simulating 500 aircraft. The variable $passengers_k$ indicates the number of passengers flying in cabin k. The variable $sellouts_k$ indicates the fraction of flights (over the 500 simulated flights) that sellout in cabin k. **CS**, **PS** and **TS** indicate average (per flight) consumer, producer and total surplus respectively.

Table 12: Counterfactual, change in the absolute number of retail sales

	Eliminating upgrades...	**Without Upgrades** Outside Option	*EC*	*BC*	*total*
With Upgrades	Outside Option	181,032	861	52	181,945
		(1,588)	(83)	(11)	(1,593)
	EC	2,050	79,200	1,013	82,263
		(315)	(1,738)	(48)	(1513)
	$EC + UP$	57	3,423	88	3,568
		(15)	(83)	(13)	(92)
	BC	132	192	10,725	11,049
		(28)	(30)	(401)	(395)
	total	183,271	83,676	11,878	
		(1,776)	(1,738)	(408)	

Notes: I simulated 500 flights under the two scenarios: with and without upgrades for 10 bootstrap samples. I reported bootstrap estimates and standard errors. I evaluate how the behavior of consumers changes when eliminating the upgrade option.

Table 13: Counterfactual, change of retail sales as percentage of original purchases

	Eliminating upgrades...	**Without Upgrades** Outside Option	*EC*	*BC*
With Upgrades	Outside Option	99.5%	0.5%	0.0%
		(0.0)	(0.0)	(0.0)
	EC	2.5%	96.3%	1.2%
		(0.4)	(0.4)	(0.1)
	$EC + UP$	1.6%	95.9%	2.5%
		(0.4)	(0.5)	(0.4)
	BC	1.2%	1.7%	97.1%
		(0.3)	(0.3)	(0.5)

Notes: I simulated 500 flights under the two scenarios: with and without upgrades for 10 bootstrap samples. I reported bootstrap estimates and standard errors. I evaluate how the behavior of consumers changes when eliminating the upgrade option in percentage terms.

Table 14: Counterfactual, consumer surplus net effects

Eliminating Upgrades ↗	Outside Option	*EC*	*BC*
Outside Option	0	-39,666	-5,386
	(0)	(8,063)	(1,983)
EC	110,666	153,748	-74,069
	(13,496)	(41,835)	(9,154)
$EC + UP$	8,132	531,122	36,301
	(2,413)	(21,090)	(5,938)
BC	174,542	15,366	-297,130
	(37,143)	(3,996)	(22,976)

Notes: I simulated 500 flights under the scenarios with and without upgrades for 10 bootstrap samples. I reported bootstrap estimates and standard errors. I evaluated consumer surplus for any passenger in all the 500 flights under the two scenarios and then consider their difference: $CS^{\text{scenario with upgrades}} - CS^{\text{scenario without upgrades}}$. Results are in \$.

Table 15: Producer surplus counterfactual, aggregate revenues across cabins

Cabin	With Upgrades	Without upgrades	Δ
EC	53.588\$	52.759\$	+829\$
	(1.299)	(1.304)	(89)
BC	24.929\$	26.139\$	-1.210\$
	(1.067)	(1.099)	(120)
UP	1.935\$	0\$	+1.935\$
	(71)	0	
total	80.452\$	78.898\$	+1.553\$
	(2.136)	(2.101)	(138.9)

Notes: I simulated 500 flights under the scenarios: with and without upgrades for 10 bootstrap samples. I reported bootstrap estimates and standard errors. I evaluate producer surplus for any flight under the scenarios with and without upgrades; then, I consider the average across the 500 flights. Results are in \$.

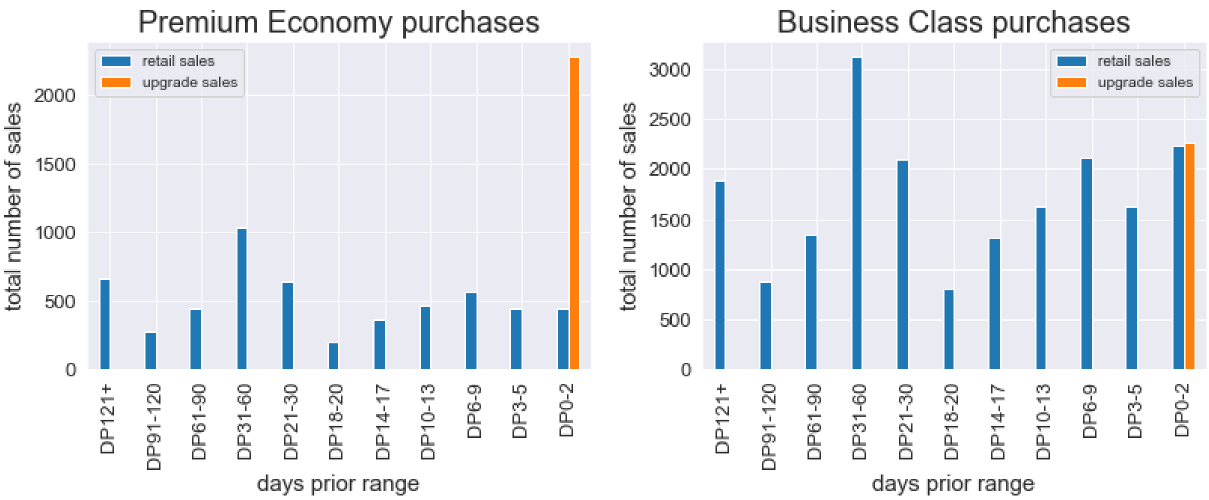
Table 16: Producer surplus counterfactual, distribution of revenues across cabins

Cabin	With Upgrades	Without upgrades
EC	0.666	0.669
	(0.007)	(0.008)
BC	0.310	0.331
	(0.007)	(0.008)
UP	0.024	0
	(0.001)	(0)

Notes: I simulated 500 flights under the scenarios: with and without upgrades for 10 bootstrap samples. I reported bootstrap estimates and standard errors. I evaluate the average distribution of producer surplus across products per scenario.

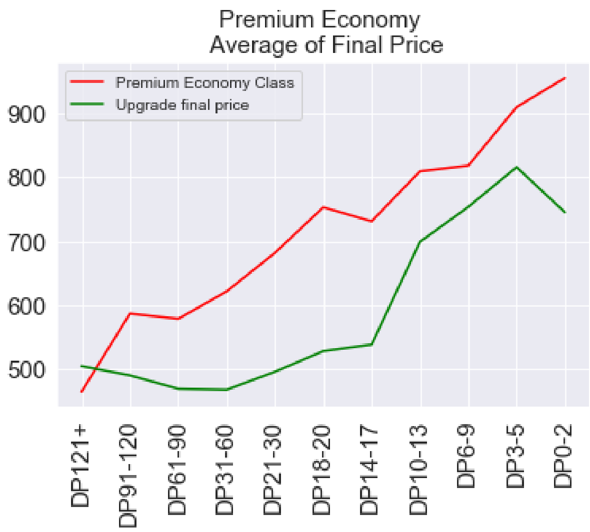
Figures

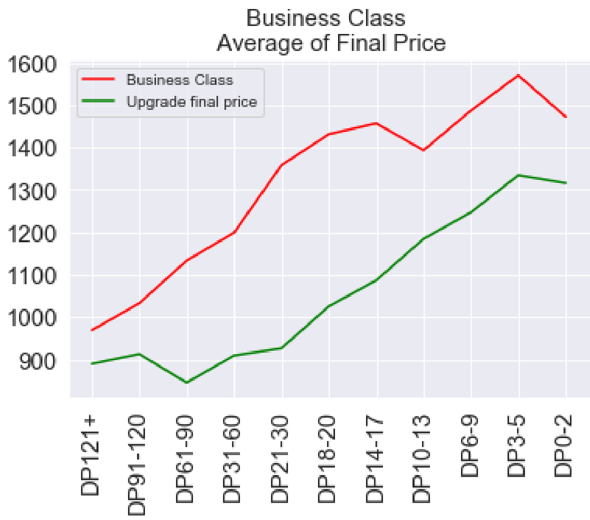
Figure 1



Notes: The horizontal axis shows the booking horizon split in periods before departure, with *DP* indicating *Days Prior* departure. The vertical axis displays the total number of tickets purchased over all flights in the dataset. I excluded travelers belonging to frequent flyer programs.

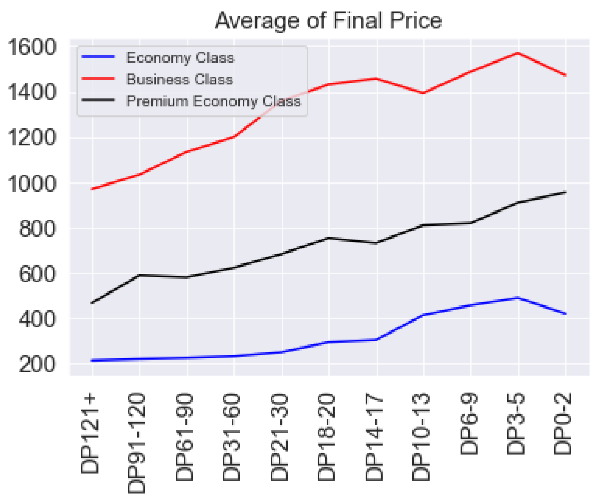
Figure 2





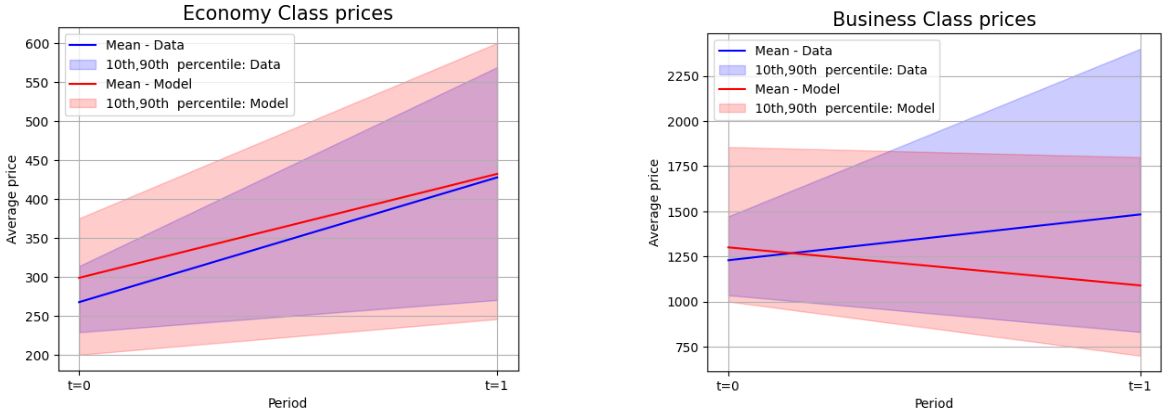
Notes: The horizontal axis shows the booking horizon split in periods before departure, with *DP* indicating *Days Prior* departure. The vertical axis displays the final paid price paid to access premium cabins. I excluded travelers belonging to frequent flyer programs.

Figure 3



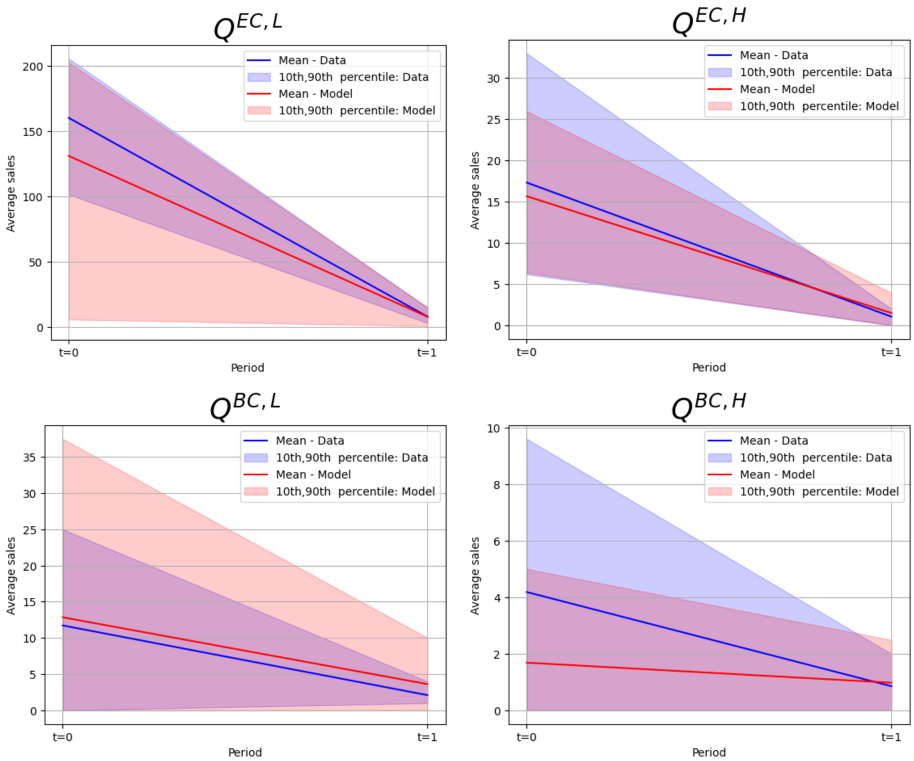
Notes: The horizontal axis shows the booking horizon split in periods before departure, with *DP* indicating *Days Prior* departure. The vertical axis displays the final paid price to access Economy, Premium Economy and Business Class with a retail sale. I excluded travelers belonging to frequent flyer programs.

Figure 4: Prices



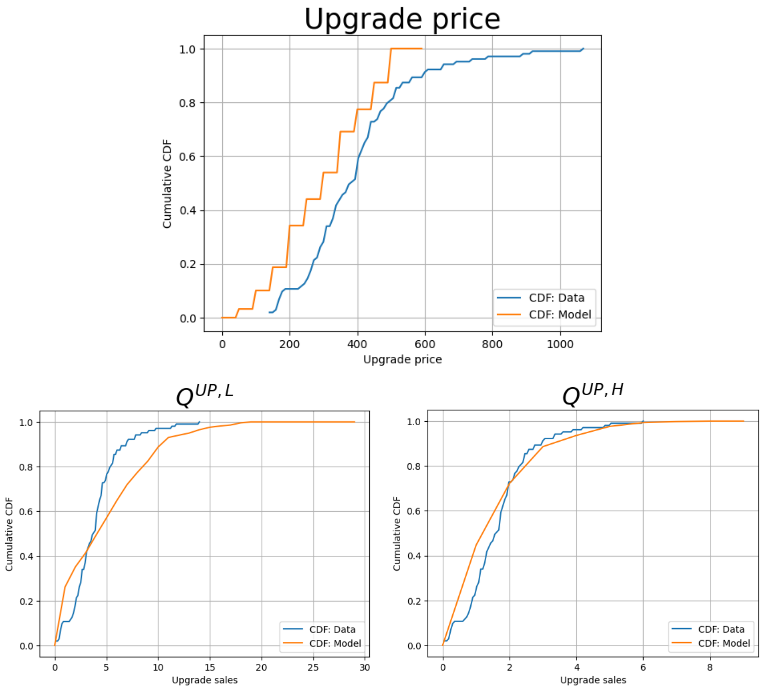
Notes: Price distribution for flights flying over the international route on aircraft with $c_{EC} = 247$ and $c_{BC} = 51$. The blue shaded area represents the 10th and 90th of the distribution of prices observed in the data. The red shaded area represents the bootstrap distribution of estimated prices: the lower bound is the average 10th percentile (across bootstrap estimates); the upper bound is the average 90th percentile (across bootstrap estimates).

Figure 5: Retail Sales



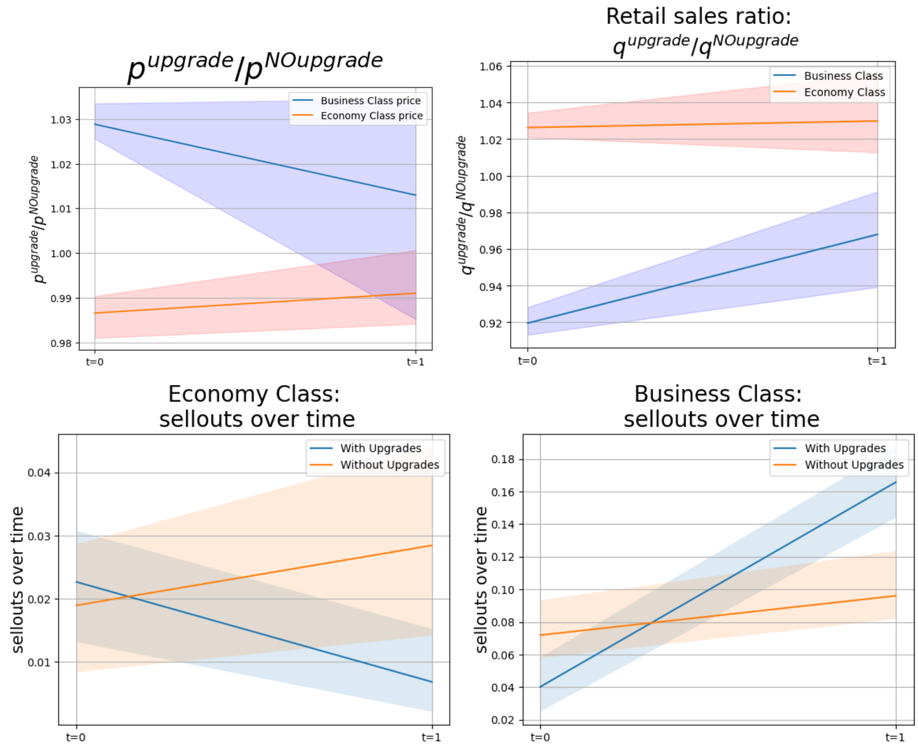
Notes: Distributions of simulated and actual retail purchases of tickets for flights over the international route on aircraft with $c_{EC} = 247$ and $c_{BC} = 51$. The blue shaded area represents the 10th and 90th of the distribution of retail sales observed in the data. The red shaded area represents the bootstrap distribution of estimated sales: the lower bound is the average 10th percentile (across bootstrap estimates); the upper bound is the average 90th percentile (across bootstrap estimates).

Figure 6: Upgrade prices and upgrade sales



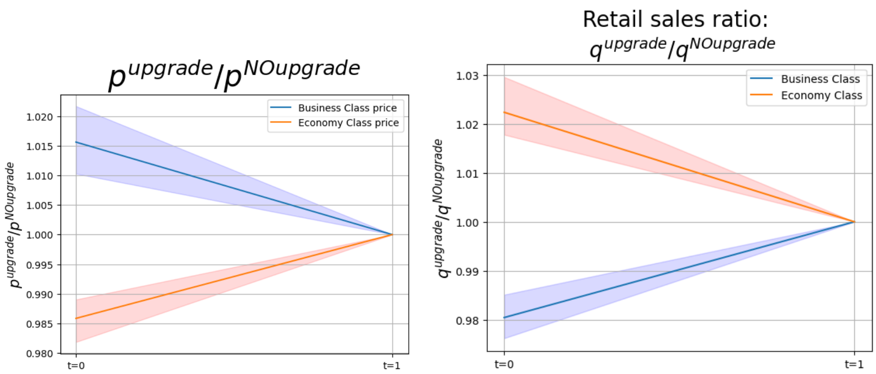
Notes: Distributions of simulated and actual price and quantities of upgrades for flights over the international route on aircraft with $c_{EC} = 247$ and $c_{BC} = 51$. The orange line represents the average CDF across bootstrap estimates.

Figure 7: Counterfactual over time with capacity constraints



Notes: I evaluated the estimates and bootstrap 95% confidence interval for large aircraft over the international route with capacity constraints. I used 10 bootstrap samples, each simulating 500 aircraft. In the sellouts picture, I report the fraction of flights experiencing sellouts in the corresponding cabin over time. Economy class sellouts decrease over time, as travelers upgrades upgrade to Business Class and leave Economy Class.

Figure 8: Counterfactual over time without capacity constraints



Notes: I evaluated the estimates and bootstrap 95% confidence interval for large aircraft over the international route without capacity constraints. I used 10 bootstrap samples, each simulating 500 aircraft.

A Appendix

A.1 Appendix - example of an upgrade notification

Figure 9: Example of a notification email for an upgrade

Notes: Email notifying for an upgrade possibility

A.2 Appendix - upgrade discount: robustness check

The evidence of regression (1) remains robust even after controlling for various confounding factors, including load factors, time and flight fixed effects. I summarize the results in Table 17 and 18.

By defining t as the time of the initial purchase (so that $t = T - 2$ indicates the second to last day of the booking horizon when the airline allows for upgrade sales) and f as the flight on which transaction i takes place, I estimate the following specification for robustness checks:

$$P_{\text{itf}} = \alpha + \beta_{\text{up}}\mathbb{I}\{\text{upgrade sale}\}_i + LF_{tf}\gamma_1 + LF_{T-2f}\gamma_2 + t\delta + FE_f + \epsilon_i \tag{15}$$

with LF_t indicating the Load Factor, defined as the ratio of realized sales up to period t to the total capacity. Similar to the analysis in Section 2.3, I estimate regression (15) separately for Business and Premium Economy Class. Results in Tables 17 and 18 show that in all of four specifications, the extent of the discount is statistically significant.

Low average final prices to access premium cabin might occur on flights experiencing few sales in premium cabin. These flights might have low prices. Therefore the discounts observed in regression (1) might capture cross flights price differences, due to variation in unsold capacity, rather than within-flight price differences. I control for this possibility in column (1), where I control for the load factor level at the time of the initial purchase. The price difference between retail and upgrade sales is still statistically different than 0.

Similarly, the airline might try to fill capacity in premium cabin on those flights with an emptier premium cabin the last two days before departure, when the upgrade program starts. Therefore, a lower level of LF_{T-2} might imply low premium cabin retail prices, thus the observed discount of regression (1) might detect a two-days before departure load factor difference across flights. This turns out not to be case, as the coefficient β_{UP} in column (2) is still statistical significant.

The difference between retail and upgrades final price paid might be due to the initial ticket purchase date. In particular, as prices tend to increase over time, it might be that most upgrading customers have made their lower cabin ticket purchase very early on over the booking horizon, when prices are typically low. This might imply low average final prices paid after an upgrade simply because of the low initial retail prices. I control for this effect in column (3), by including a time trend effect. The price difference between retail and upgrade sales remains statistically different than 0.

Finally, I jointly consider the load factor, time and flight fixed effect. I include flight fixed effects, as upgrades might take place on specific flights, that for unobserved idiosyncratic reasons might display low premium seats' prices. Even with these controls, the price difference between retail and upgrade sales is still statistically different than 0.

Table 17: Business Class

Variable	estimate (1)	estimate (2)	estimate (3)	estimate (4)
Average retail price (no upgrade)	1,040.30***	1068.92***	1,437.07***	1,150.04***
	(12.87)	(31.11)	(16.22)	(153.92)
Savings due to upgrade	-166.86***	-144.03***	-197.19***	-200.60***
	(14.35)	(14.18)	(15.47)	(19.86)
LF_t	yes	no	no	yes
LF_{T-2}	no	yes	no	no
t	no	no	yes	yes
Flight FE	no	no	no	yes

Notes: Results are in $ and computed using sales of Business Class seats. I dropped sales to customers with flyers-ID and sales with auction upgrade. Standard Errors are in parenthesis: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the flight-level.

Table 18: Premium Economy Class

Variable	estimate (1)	estimate (2)	estimate (3)	estimate (4)
Average retail price (no upgrade)	526.49***	588.21***	786.88***	529.31***
	(8.30)	(16.20)	(5.80)	(12.13)
Savings due to upgrade	-112.24***	-115.76***	-149.61***	-111.13***
	(7.43)	(8.53)	(7.42)	(7.53)
LF_t	yes	no	no	yes
LF_{T-2}	no	yes	no	no
t	no	no	yes	yes
Flight FE	no	no	no	yes

Notes: Results are in $ and computed using sales of Premium Economy Class seats. I dropped sales to customers with flyers-ID and sales with auction upgrade. Standard Errors are in parenthesis: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the flight-level.

A.3 Appendix - supply model: derivative decomposition

In this section, I describe the effects of a price change in $t = 0$ on expected revenues in $t = 1$. First, recall $\tilde{\mathbb{E}}[V(\omega_1)]$, as in Section 3.3:

$$\tilde{\mathbb{E}}[V(\omega_1)] = \mathbb{E}\Big[\sum_{c_{1,BC},Q^H_{0,EC},Q^L_{0,EC}} \mathbb{P}(c_{1,BC}, Q^H_{0,EC}, Q^L_{0,EC}|\omega_0, p_{0,EC}, p_{0,BC})\mathbb{E}[V(\omega_1)]\Big]$$
$$= \mathbb{E}\Big[\sum_{\eta} q(\eta)\mathbb{E}[V(\omega_1)]\Big]$$

where, for simplicity of notation, I rewrite the transition probability (conditional on a specific realization of $[\omega_0, p_{0,EC}, p_{0,BC}]$) as $q(\eta)$, with $\eta = [c_{1,BC}, Q^H_{0,EC}, Q^L_{0,EC}]$.

Let's consider $\frac{d\tilde{\mathbb{E}}[V(\omega_1)]}{dp_{0,BC}}$:

$$\frac{d\tilde{\mathbb{E}}[V(\omega_1)]}{dp_{0,BC}} = \underbrace{\mathbb{E}\left[\sum_{\eta} \frac{dq(\eta)}{dp_{0,BC}}\mathbb{E}[V(\omega_1)]\right]}_{(1)} + \mathbb{E}\left[\sum_{\eta} q(\eta)\left(\underbrace{\mathbb{E}\left[\sum_{\tilde{c}_{BC}} \frac{dPr(\tilde{c}_{BC}|\omega_1)}{dp_{0,BC}} Q_{UP}\right]}_{(2)} + \mathbb{E}\left[\sum_{\tilde{c}_{BC}} Pr(\tilde{c}_{BC}|\omega_1)\underbrace{\frac{d\tilde{Q}_{UP}}{dp_{0,BC}}}_{(3)}\right]\right)\right].$$

An increase in $p_{0,BC}$ has three effects on $\tilde{\mathbb{E}}[V(\omega_1)]$: (1) it affects the transition probability, given a change in distribution of $t = 0$ retail sales. (2) It modifies the probability of an emptier Business Class at the end of $t = 1$, thus it affects the number of potentially upgrading customers. (3) It modifies the probability that an Economy Class ticket holder purchases an upgrade.

A.4 Appendix - identification argument - intuition

As discussed in Section 4.2, I identify demand shocks at the flight-level by using both demand and supply side restrictions. Then, by assuming that demand shocks follow specific parametric distributions, I identify these distributions at the route-level, based on similar restrictions. Given the complexity of the model described in Section 3, I cannot provide a formal proof of a one-to-one mapping between observables and model primitives. In particular, I am unable to find closed form solutions for the optimal price vector. Here, I provide an intuitive identification argument for a simplified version of the model.

A.4.1 Appendix - flight-level identification

In this section, I consider a monopolistic airline selling tickets in only one cabin at price p; the firm is active in one period and does not face any capacity constraint. On the demand side, I assume that the market size, N, is stochastic, $N \sim Po(\lambda)$, and that each individual i features the following utility function:

$$u_i = \begin{cases} v_i - p & \text{purchase} \\ 0 & \text{no purchase} \end{cases}$$

where $v_i \sim U[1, B]$ is individual i's willingness to pay. Customer i buys the product if $v_i - p \geq 0$. Given *iid* customers, the choice probability is $s(p) = \frac{B-p}{B-1}$. Optimality of price requires $p = \frac{B}{2}$.

Consistently with the broader discussion of Section 4.2, the data displays both price and quantity (number of sales), p^o and Q^o. I can uniquely identify B and λ from observing p^o and Q^o. As a preliminary step, I consider the observed number of sales, given demand shock B and price p, as generated from $Q^o = \lambda \frac{B-p}{B-1} + \epsilon$, where $\lambda \frac{B-p}{B-1}$ is the average number of sales (given the demand shock and the optimal price) and ϵ represents a mean 0 error induced by the randomness of the market size. Then, by taking expectations (over all flights with the same demand shock and price), I obtain $\mathbb{E}[Q^o] = \mathbb{E}[\lambda \frac{B-p}{B-1} + \epsilon] = \lambda \frac{B-p}{B-1}$. Then, the solution (for B and λ) of system (16) is $B = 2p^o$ and $\lambda = 2\mathbb{E}[Q^o]$.

$$\begin{cases} \mathbb{E}[Q^o] = \lambda \frac{B-p^o}{B-1} \\ p^o = \frac{B}{2} \end{cases} . \tag{16}$$

Describing the demand side with two parameters only is the crucial identifying assumption. This ensures that the number of restrictions is at least as large as the number of parameters.

A.4.2 Appendix - route-level identification

Based on the previous argument, I can identify flight-level demand shocks and arrival rate. In practice, estimating all these shocks requires estimating them for any flight. This is not feasible due to the large number of flights in the data. I assume they are drawn from a known parametric distribution. This assumption reduces the number of parameters to estimate. Going back to identification: since flight-level identification is possible, route-level identification, under parametric assumption, is obvious. However, here I give a formal intuition for the identifying moments.

For simplicity, let's assume that $B \sim U[2, C]$ and λ being constant[24] across flights. Let's assume the dataset includes M flights f, so that it is $\{p_f^o, Q_f^o\}_{f \in \{1,\dots,M\}}$. With the same notation as in Section A.4.1, I can establish the following restrictions:

$$\begin{cases} \mathbb{E}[Q_f^o] = \lambda \frac{B_f - p_f^o}{B_f - 1} \\ p_f^o = \frac{B_f}{2} \end{cases}.$$

Given the random coefficient structure on the demand shock, I consider the expectation of quantities and prices across flights. It follows that[25]:

$$\mathbb{E}[Q_f^o] = \mathbb{E}_B \left[\mathbb{E}[Q_f^o | B] \right] = \lambda \frac{C - 2 + \log(C-1)}{2(C-2)},$$

and

$$\mathbb{E}[p_f^o] = \mathbb{E}_B \left[\frac{B}{2} \right] = \frac{C+2}{4}.$$

From the expected value of prices across flights I can identify C, then from the expected value of sales identification of λ follows. As discussed in Section 4.2, the expected number of sales identifies arrival rate, whereas the expected value of prices identifies the willingness to pay[26].

[24] Even if λ is constant across flights, the model generates variation in observed quantity across flights due to demand shocks. Another way to have quantity variation in the model is to include a random coefficient specification for λ. In such a case, each flight would be featured by both a demand shock and an arrival rate shock.

[25] By plugging optimal prices into $\mathbb{E}[Q_f^o]$, it follows that $\mathbb{E}[Q_f^o] = \lambda \frac{B_f - \frac{B_f}{2}}{B_f - 1} = \frac{\lambda B_f}{2(B_f - 1)}$. Then, $\mathbb{E}[Q_f^o] = \mathbb{E}_{B_f} \left[\mathbb{E}[Q_f^o | B_f] \right] = \int_2^C \frac{\lambda B_f}{2(B_f-1)} \frac{1}{C-2} dB_f = \frac{\lambda}{2(C-2)} [x + \log(x-1)]_{x=2}^{x=C}$.

[26] In Section 4.2, I use the distribution of prices, since I also need to identify the variance of the WTP.

A.5 Appendix - estimation: the role of inattention parameters (α_L, α_H) with no capacity constraints

In this section, I analyze the effects of the upgrade option in case of fully attentive Economy Class ticket holders when the airline does not face capacity constraints. The sequential price discrimination effect on $t = 0$ customer is larger than with inattentive travelers. In particular, since the probability that Economy Class ticket holders buy an upgrade increases, the opportunity cost of both raising Business Class prices and decreasing Economy Class prices decreases. Indeed by charging higher Business Class and lower Economy Class prices, the number of Economy Class ticket buyers increase, thereby increasing the number of upgrading customers.

Table 19: Role of upgrades with attentive customers and without capacity constraints

	With Upgrades		Without upgrades
	Attentive travelers	Inattentive travelers	
	$\alpha_H = \alpha_L = 1$	$\alpha_H = 0.2, \alpha_L = 0.1$	
	(1)	(2)	(3)
$p_{EC,0}$	282	313	317
	(2.8)	(2.95)	(2.49)
$p_{EC,1}$	430	430	430
	(5.28)	(5.28)	(5.28)
$p_{BC,0}$	1,238	1,152	1,134
	(12.56)	(14.23)	(11.96)
$p_{BC,1}$	848	848	848
	(15.61)	(15.61)	(15.61)
p_{UP}	242	268	
	(115)	(115)	
$passengers_{EC}$	98.09	145.69	150.27
	(1.83)	(2.25)	(2.82)
$passengers_{BC}$	106.68	42.36	35.13
	(1.77)	(1.73)	(1.61)
upgrades	78.62	7.78	
	(0.99)	(0.25)	

Notes: I evaluated the estimates and bootstrap standard errors for large aircraft over the international route, when there are no capacity constraints, under the case all travelers are attentive to the upgrade option (Column (1)) and under the case only the estimated fraction of travelers are attentive to the upgrade option (Column (2)). I used 10 bootstrap samples, each simulating 500 aircraft. The variable $passengers_k$ indicates the number of passengers flying in cabin k.

A.6 Appendix - counterfactual benchmarks: uniform pricing and free upgrades

In this section, to benchmark welfare gains of the upgrade option within the literature, I consider two other scenarios: uniform pricing and free upgrades. Results in Table 20 show that, as the airline increases its pricing flexibility, both revenues and consumer surplus increase.

Table 20: Counterfactual - various scenarios

	With Upgrades (1)	Without upgrades (2)	Uniform Pricing (3)	Free Upgrades (4)
$p_{EC,0}$	303	308	317	308
	(3.33)	(2.95)	(2.58)	(2.95)
$p_{EC,1}$	418	422	317	422
	(5.29)	(5.64)	(2.58)	(5.64)
$p_{BC,0}$	1,305	1,268	1,156	1,268
	(12.77)	(11.32)	(6.1)	(11.32)
$p_{BC,1}$	996	983	1,156	983
	(13.92)	(24.15)	(6.1)	(24.15)
p_{UP}	297			0
	(134)			0
$passengers_{EC}$	164.5	167.2	168.74	153.55
	(2.85)	(3.24)	(2.86)	(3.23)
$passengers_{BC}$	29.3	23.82	20.51	37.47
	(0.86)	(0.83)	(0.84)	(0.66)
$upgrades$	7.11			13.64
	(0.19)			(0.26)
$sellout_{EC}$	0.01	0.03	0.04	0.01
	(0.004)	(0.009)	(0.011)	(0.003)
$sellout_{BC}$	0.166	0.096	0.095	0.354
	(0.016)	(0.015)	(0.014)	(0.022)
CS	81,978	80,751	80,156	83,645
	(3,017)	(3,049)	(3,016)	(3,013)
PS	80,451	78,897	77,823	78,897
	(2,251)	(2,214)	(2,188)	((2,214))
TS	162,430	159,649	157,980	162,544
	(5,244)	(5,239)	(5,177)	(5,203)

Notes: I evaluated the estimates and bootstrap standard errors for large aircraft over the international route. I used 10 bootstrap samples, each simulating 500 aircraft. The variable $passengers_k$ indicates the number of passengers flying in cabin k. The variable $sellouts_k$ indicates the fraction of flights (over the 500 simulated flights) that sellout in cabin k. **CS**, **PS** and **TS** indicate average (per flight) consumer, producer and total surplus respectively.

The scenario of uniform pricing (Column (3)) considers a restrictive pricing regime, where the airline sets a constant price over time for the two cabins in $t = 0$ after the realization of the initial demand shock, and no upgrades are allowed. Being the firm constrained in its pricing decisions, producer surplus is lower than in the scenario without upgrades (Column (2)). Relatively low Business Class prices in $t = 0$ leads to early sellouts in premium cabin, whereas low Economy Class prices in $t = 1$ leads to sellouts in lower cabin at the end of $t = 1$. Overall, early Business Class sellouts prevents high-value $t = 1$ customers from enjoying high-quality products in $t = 1$, thereby leading to smaller consumer surplus, with respect to the situation of dynamic pricing without upgrades. Results on prices, sellouts and total surplus align with the analysis of Williams (2022).

The second scenario involves the airline offering upgrades for free (Column (4)) while implementing dynamic pricing. With free upgrades, the upgrade option does not modify the opportunity cost of selling any seat in any period. Consequently, the airline pricing problem is the same as in the scenario without upgrades (Column (2)). As the airline cannot capture surplus from upgrading customers, upgrades only benefit customers. This leads to the highest levels of total surplus among all the counterfactual scenarios.

When the firm implements dynamic pricing, the introduction of the upgrade option increases producer surplus by 2%; transitioning from a uniform pricing regime to dynamic pricing results in a 1.3% increase in revenues. My model predicts that upgrades are relatively more important in increasing revenues than dynamic pricing. This result is primarily driven by the two-period assumption of the model. With more time periods, dynamic pricing would likely yield higher gains as the airline could employ better intertemporal and intratemporal price discrimination strategies over customers with varying demands over time[27]. Additionally, with more than two periods, the scope of the upgrade option would be diminished, as the airline would aim at extracting surplus in the booking horizon through dynamic pricing rather than relying on the last day upgrades. Thus, counterfactual results presented in this paper serve as an upper bound on the effects of the upgrade option.

[27] As a benchmark in the literature, Williams (2022) finds that dynamic pricing increases revenues by 8% in a four period model and one cabin.

A.7 Appendix - counterfactual results: the role of demand shocks

In this section, I complement the evidence regarding the effects of the upgrade option arising from various demand shocks of Tables 8, 9, and 10, by showing how different realizations of initial demand shocks lead to variation in upgrades sales, prices and surplus. Overall, as the demand shock increases, p_{UP} increases and the number of upgrading travelers increases. Concurrently, producer and consumer surplus increase with the size of the demand shock.

Table 21: Leisure type demand shock and upgrades

Demand Shock	Average p_{UP}
H,H	437.626
	(26.806)
H,M	353.364
	(13.033)
M,H	400.284
	(10.213)
H,L	201.505
	(32.788)
L,H	298.517
	(24.283)
M,M	286.710
	(6.956)
M,L	226.218
	(31.344)
L,M	257.299
	(8.939)
L,L	257.919
	(23.094)

Demand Shock	Average q_{UP}
H,H	6.132
	(1.134)
H,M	6.997
	(0.549)
M,H	6.662
	(0.383)
H,L	8.287
	(1.703)
L,H	6.275
	(0.850)
M,M	8.721
	(0.334)
M,L	6.228
	(0.650)
L,M	5.358
	(0.612)
L,L	3.370
	(0.518)

Notes: I simulated 500 flights operating in the international route under the scenario with upgrades. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. I evaluate the optimal upgrade price and corresponding realized upgrade sales. Bootstrapped standard errors over 10 samples are recorded.

Table 22: Leisure type demand shock and upgrades

Demand Shock	Change in PS
H,H	1,844.5
	(1,092.2)
H,M	1,766.0
	(367.1)
M,H	1,521.7
	(475.4)
H,L	1,179.7
	(222.4)
L,H	2,362.9
	(650.4)
M,M	1,981.8
	(217.9)
M,L	835.0
	(122.6)
L,M	1,164.7
	(214.0)
L,L	534.7
	(235.8)

Demand Shock	Change in CS
H,H	1,641.1
	(1,737.9)
M,H	1,687.4
	(830.6)
H,M	430.9
	(717.7)
H,L	978.8
	(177.8)
L,H	4,098.5
	(1,011.3)
M,M	1,415.0
	(244.8)
M,L	838.0
	(306.5)
L,M	1,002.9
	(386.4)
L,L	331.9
	(269.7)

Notes: I simulated 500 flights operating in the international route under the scenarios with and without upgrades. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. I evaluate surplus in both scenarios and take the difference, for example *Change in* $PS = PS^U - PS^{NoU}$, with PS^U is the producer surplus in the scenario with the upgrade option and PS^{NoU} is the producer surplus in the scenario without it. Bootstrapped standard errors over 10 samples are recorded.

A.8 Appendix - estimation: the role of inattention

In this section, I show estimation results under the assumption that all customers pay attention to the email, sent by the airline, regarding the upgrade option. The focus is on the large aircraft flying over the international route.

Moments used for estimation are the same as those in Section 4.3, and the simulated model restricts $\alpha_H = \alpha_L = 1$ to assume fully attentive travelers. Estimation results are slightly different than those reported in Section 4.3 and, visually, assuming fully attentive travelers leads to a worse model fit. When assuming fully attentive travelers, the model implies a larger number of upgrading customers, which modifies the airline pricing strategies, by inducing higher Business Class prices over the booking horizon, with respect to the scenario with inattentive customers. Since sales are generated together with prices in the simulation routine, demand estimates reported in Table 23 and 24 are different than those in Tables 4 and 5.

Table 23: Preferences - international route, attentive customers

t=0		*t=1*	
parameter	*estimate*	*parameter*	*estimate*
(μ_{H0}, σ_{H0})	(314.24,94.24)	(μ_{H1}, σ_{H1})	(314.24,94.24)
	((45.64),(45.64))		((45.64),(45.64))
κ_{H0}	3.23	κ_{H1}	2.95
	(0.0)		(0.01)
(μ_{L0}, σ_{L0})	(324.39,193.08)	(μ_{L1}, σ_{L1})	(324.39,220.05)
	((8.72),(136.72))		((8.72),(25.0))
κ_{L0}	3.5	κ_{L1}	3.27
	(0.0)		(0.0)

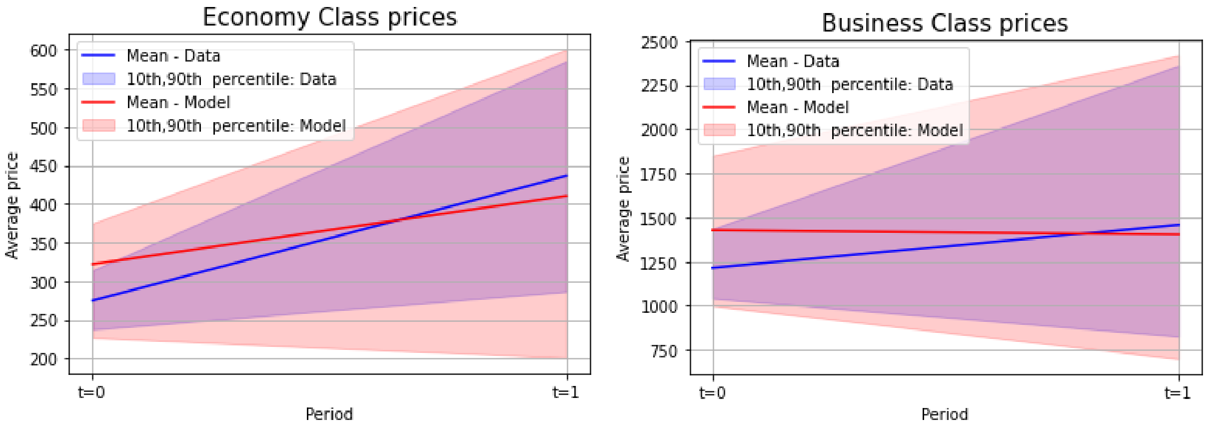
Notes: Parameters for flights in the international route on aircraft with $c_{EC} = 247$, $c_{PE} = 21$, $c_{BC} = 30$. In the simulated airline problem, Business Class includes Premium Economy. In parenthesis I report bootstrap standard errors. I use 100 bootstrap samples, by resampling at the flight-level.

Table 24: Arrival process and inattention - international route, attentive customers

parameter	*estimate*
λ_0	512.0
	(0)
λ_1	42.45
	(3.9)
θ_0	0.07
	(0.0)
θ_1	0.13
	(0.0)

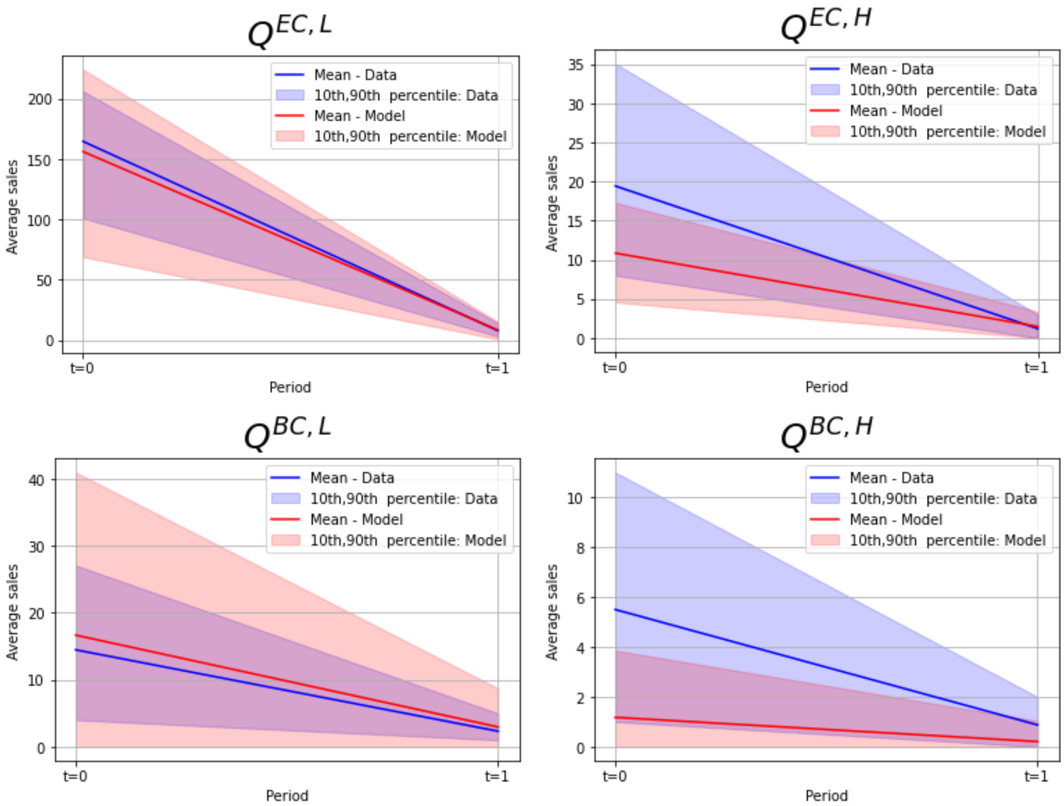
Notes: Parameters for flights in the international route on aircraft with $c_{EC} = 247$, $c_{PE} = 21$, $c_{BC} = 30$. In the simulated airline problem, Business Class includes Premium Economy. In parenthesis I report bootstrap standard errors. I use 100 bootstrap samples, by resampling at the flight-level.

Figure 10: Prices - international route, attentive customers



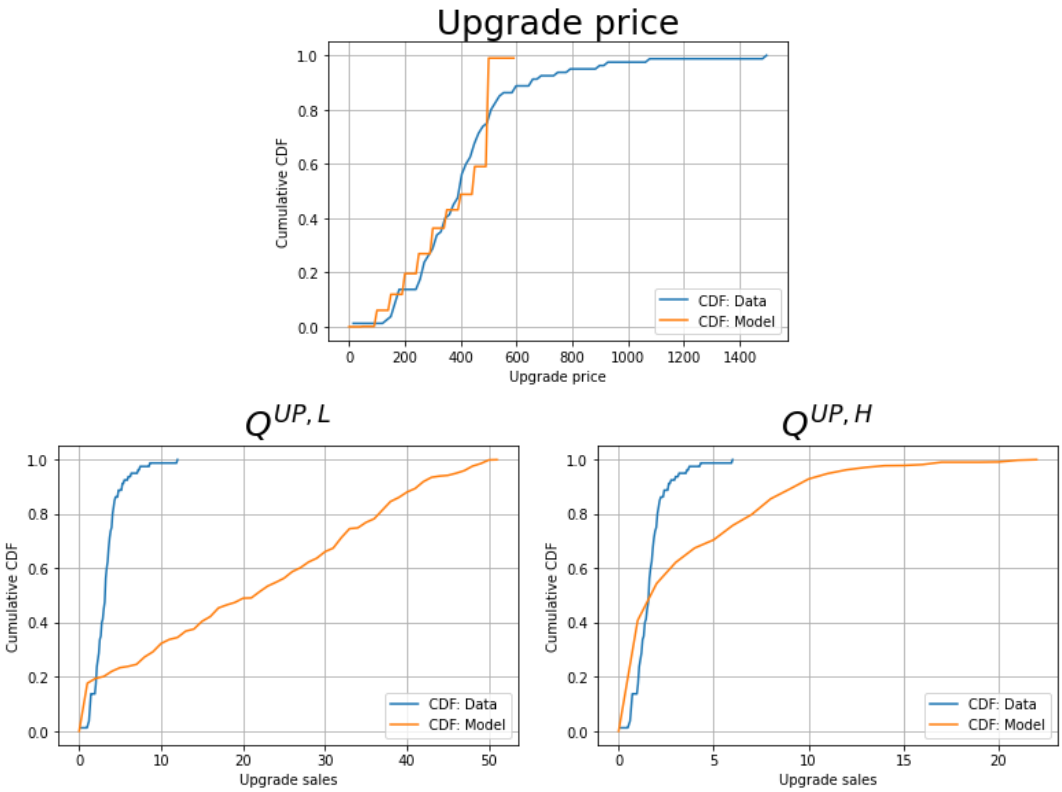
Notes: Simulated and actual price distributions for flights over the international route on aircraft with $c_{EC} = 247$, $c_{PE} = 21$, $c_{BC} = 30$. In the simulated airline problem, Business Class includes Premium Economy.

Figure 11: Retail sales - international route, attentive customers



Notes: Simulated and actual price distributions for flights over the international route on aircraft with $c_{EC} = 247$, $c_{PE} = 21$, $c_{BC} = 30$. In the simulated airline problem, Business Class includes Premium Economy.

Figure 12: Upgrade sales and prices - international route, attentive customers



Notes: Distributions of simulated and actual price and quantities of upgrades for flights over the international route on aircraft with $c_{EC} = 247$, $c_{PE} = 21$,$c_{BC} = 30$. In the simulated airline problem, Business Class includes Premium Economy.

A.9 Appendix - small aircraft size

A.9.1 Appendix - distribution of aircraft size and upgrades

The number of upgrades varies based on the size of the aircraft. This paper does not delve into the discussion of how the airline deploys different aircraft on different routes; instead, I considered it as exogenously determined.

The dataset used in this study consists of 11 types of aircraft, each varying in terms of capacity for Economy, Premium Economy, and Business Class. The largest aircraft, which belongs to the Boeing 787 Dreamliner family, has a total of 247 seats in Economy Class, with 21 seats in Premium Economy Class (c_{PE}) and 30 seats in Business Class (c_{BC}). On the other hand, the smallest aircraft, the Boeing 757-200, does not have a Premium Economy Class and features 153 seats in Economy Class (c_{EC}) and 16 seats in Business Class (c_{BC}). Analysis of the data, as shown in Table 25, reveals that the airline tends to deploy larger aircraft on the international route. Moreover, Table 1 illustrates that the majority of upgrades occurs between Economy and Premium Economy Classes, leading to a higher number of upgrades on larger aircraft.

Table 25: Distribution of upgrades relative to aircraft size

	Domestic Route			International Route		
aircraft size	*upgrades*	*flights*	*upgrades per flight*	*upgrades*	*flights*	*upgrades per flight*
Large	58	15	3.8	1.932	294	6.5
Small	231	284	0.8	366	329	1.1

Notes: I reported the distribution of the largest (labeled "Large", with $c_{EC} = 247, c_{PE} = 21, c_{BC} = 31$) and smallest aircraft (named "Small", with $c_{EC} = 153, c_{BC} = 16$) over the two routes. I also show the total number of upgrades per aircraft type.

A.9.2 Appendix - estimation: small aircraft

In this section, firstly, I present the estimation results of consumers' preferences, arrival rate, type mixture, and inattention coefficients for the smallest aircraft in the data, which operates on the domestic route. Then I show how the estimated model fits the data.

Estimation results[28] and fit for the small aircraft align with those of the larger aircraft. However, due to lower observed prices' mean and variances on the domestic route, travelers exhibit lower mean and variances for both willingness to pay and value for comfort compared to the international route. Additionally, since the small aircraft has fewer seats, the expected arrival rate is lower than that of the international route. Notably, estimates for inattention coefficients are similar to those observed on the international route. Figures 13, 14 and 15 display how the model fits the observed prices, retail sales and upgrades. Visually, the estimated model approximates the data well, even if it predicts lower than observed upgrade prices.

[28] In the original dataset there are 284 small sized flights over the domestic route. Similarly as in the case of large aircraft, discussed in Footnote 15, I estimate the model on a subset of flights in order to attain higher speed in the simulation algorithm. I estimate the model on flights with $p_{EC,0} \in [200, 400]$,$p_{EC,1} \in [250, 650]$, $p_{BC,0} \in [300, 1100]$ and $p_{BC,1} \in [400, 1500]$. The final sample is made of 79 flights.

Table 26: Preferences - small aircraft over the domestic route

t=0		*t=1*	
parameter	*estimate*	*parameter*	*estimate*
(μ_{H0}, σ_{H0})	(319.6,119.5)	(μ_{H1}, σ_{H1})	(319.6,119.5)
	((2.81),(2.19))		((2.81),(2.19))
κ_{H0}	1.96	κ_{H1}	1.91
	(0.02)		(0.04)
(μ_{L0}, σ_{L0})	(230.0,140.0)	(μ_{L1}, σ_{L1})	(230.0,229.9)
	((0.0),(0.0))		((0.0),(1.0))
κ_{L0}	2.27	κ_{L1}	2.1
	(0.0)		(0.0)

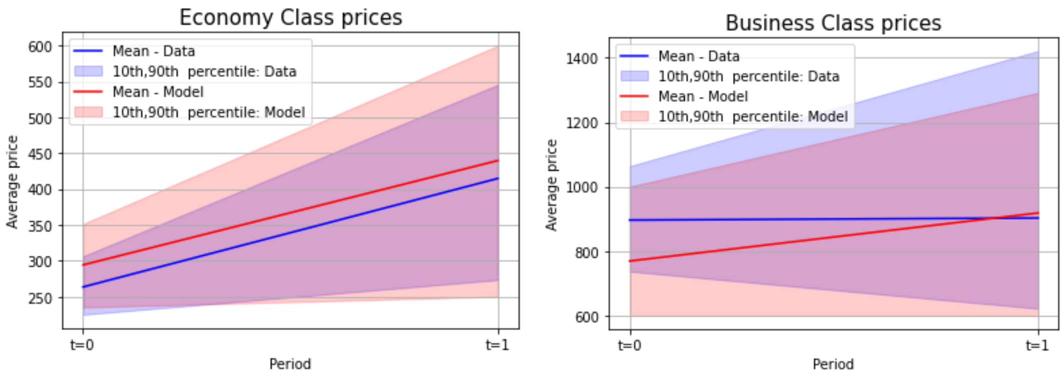
Notes: Bootstrap estimates and standard errors for flights in the domestic route on aircraft with $c_{EC} = 153$ and $c_{BC} = 16$. The data used for estimation includes 79 flights. I use 100 bootstrap samples, by resampling at the flight-level.

Table 27: Arrival process and inattention - small aircraft over the domestic route

parameter	*estimate*
λ_0	300
	(0.0)
λ_1	20.3
	(1.71)
θ_0	0.1
	(0.01)
θ_1	0.2
	(0.0)
α_H	0.19
	(0.01)
α_L	0.1
	(0.01)

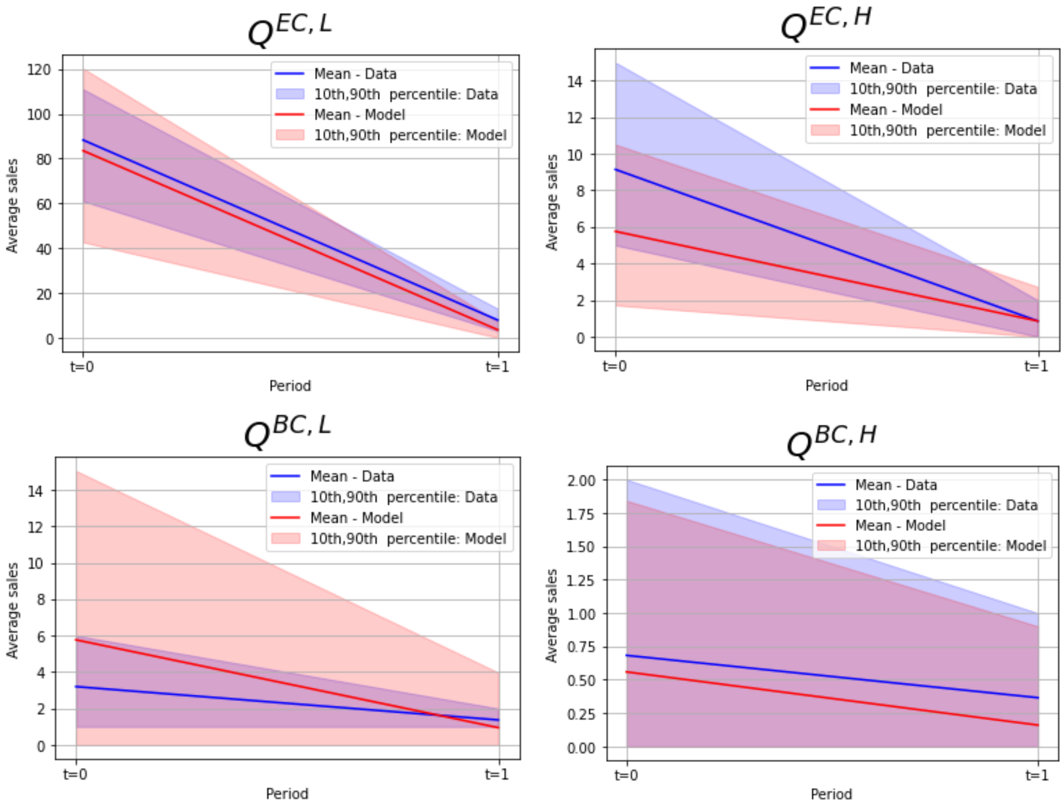
Notes: Bootstrap estimates and standard errors for flights in the domestic route on aircraft with $c_{EC} = 153$ and $c_{BC} = 16$. The data used for estimation includes 79 flights. I use 100 bootstrap samples, by resampling at the flight-level.

Figure 13: Prices - small aircraft over the domestic route



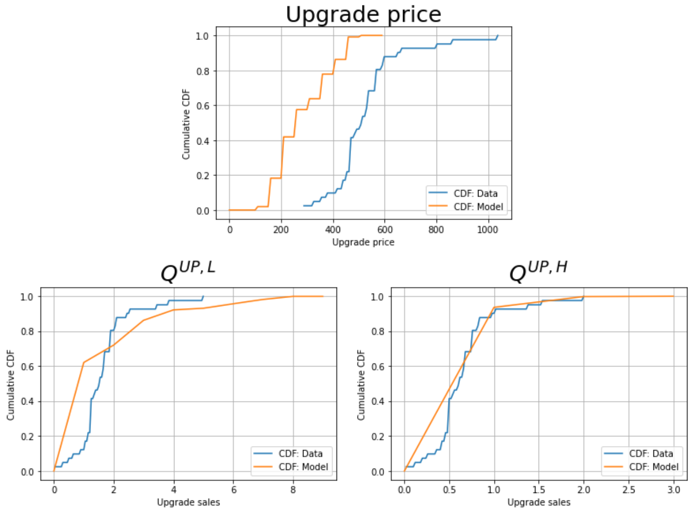
Notes: Simulated and actual price distributions for flights over the domestic route on aircraft with $c_{EC} = 153$ and $c_{BC} = 16$.

Figure 14: Retail sales - small aircraft over the domestic route



Notes: Simulated and actual price distributions for flights over the domestic route on aircraft with $c_{EC} = 153$ and $c_{BC} = 16$.

Figure 15: Upgrades sales and prices - small aircraft over the domestic route



Notes: Distributions of simulated and actual price and quantities of upgrades for flights over the domestic route on aircraft with $c_{EC} = 153$ and $c_{BC} = 16$.

A.9.3 Appendix - counterfactual: small aircraft

In this section, I assess the welfare consequences of the upgrade option in the context of small aircraft by counterfactual simulation. These results offer robustness to those presented in Section 5. Firstly, I show that the upgrade option modifies the pricing strategy of the airline on small aircraft in a similar way as on large aircraft. Then, I discuss the aggregate welfare consequences of upgrades and their distributional welfare consequences.

Economics of upgrades on small aircraft

Similarly as Table 6, Table 27 shows the effects of the introduction of the upgrade option with and without capacity constraints, as a way to distinguish sequential price discrimination from inventory management. The scenario without capacity constraints illustrates how the upgrade option works as a way to sequentially price discriminate $t = 0$ travelers. When the airline faces capacity constraints, upgrades work both as a way to price discriminate and manage inventory. In particular, with capacity constraints, the percentage change in $t = 0$ Business Class prices due to the introduction of the upgrade option is larger than without capacity constraints. In this way, the airline reduces initial sellouts in Business Class. Higher $t = 0$ Business Class prices increase the number of travelers switching from the premium product to Economy Class. In turn, this reduces airline incentives to decrease initial Economy Class prices so that the percentage decrease in

Economy Class prices with capacity constraints is lower than without them.

Table 27: Counterfactual in levels - small aircraft over the domestic route

	WITH capacity constraints		WITHOUT capacity constraints	
	With upgrades (1)	Without upgrades (2)	With upgrades (3)	Without upgrades (4)
$p_{EC,0}$	287	289	318	322
	(4.35)	(3.9)	(4.69)	(4.67)
$p_{EC,1}$	401	406	423	423
	(5.8)	(6.25)	(6.92)	(6.92)
$p_{BC,0}$	955	919	798	783
	(9.46)	(10.53)	(8.23)	(8.99)
$p_{BC,1}$	805	785	715	715
	(10.08)	(7.71)	(6.08)	(6.08)
p_{UP}	204		141	
	(124)		(80)	
$passengers_{EC}$	88.35	90.02	66.64	68.1
	(1.72)	(1.67)	(1.58)	(1.62)
$passengers_{BC}$	9.45	7.09	21.25	18.67
	(0.22)	(0.27)	(1.05)	(1.04)
$upgrades$	3.34		3.5	
	(0.11)		(0.01)	

Notes: I evaluated the estimates and bootstrap standard errors for small aircraft over the domestic route. I used 20 bootstrap samples, each simulating 500 aircraft. The scenario with capacity constraints considers $c_{EC} = 153$ and in Business Class is $c_{BC} = 16$. The variable $passengers_k$ indicates the number of passengers flying in cabin k. The variable $sellouts_k$ indicates the fraction of flights (over the 500 simulated flights) that sellout in cabin k. **CS**, **PS** and **TS** indicate average (per flight) consumer, producer and total surplus respectively.

Table 28 shows how the upgrade option works conditional on $t = 0$ leisure type demand shocks. Similarly as in Table 7, it shows two facts. Firstly, airline's incentives to increase Business Class prices after the introduction of the upgrade option are stronger when the airline faces capacity constraints and a high demand shock (HH, HM, MH) realizes. In this way the airline reduces initial period sellouts for the premium product. Secondly, when facing low demand shocks (LM, ML), the upgrade option mainly works as a way to sequentially price discriminate $t = 0$ customers and its effects with or without capacity constraints are similar, since capacity constraints almost never bind.

Table 28: Price change, sequential price discrimination and inventory management - small aircraft over the domestic route

	Overall change		Change due to SPD	
Demand shock	$\Delta p_{0,EC}$	$\Delta p_{0,BC}$	$\Delta p_{0,EC}$	$\Delta p_{0,BC}$
H,H	-0.004	0.042	0.001	0.012
	(0.008)	(0.023)	(0.003)	(0.015)
H,M	0.010	0.065	0.000	0.028
	(0.005)	(0.017)	(0.000)	(0.010)
M,H	-0.011	0.103	-0.033	0.034
	(0.016)	(0.030)	(0.013)	(0.011)
H,L	-0.000	0.018	0.000	0.011
	(0.005)	(0.019)	(0.000)	(0.015)
L,H	-0.037	0.037	-0.040	0.039
	(0.024)	(0.024)	(0.022)	(0.022)
M,M	-0.004	0.062	-0.013	0.026
	(0.006)	(0.013)	(0.007)	(0.011)
M,L	0.000	0.011	-0.001	0.031
	(0.002)	(0.017)	(0.003)	(0.019)
L,M	-0.007	0.007	-0.008	0.008
	(0.006)	(0.006)	(0.008)	(0.008)
L,L	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: I simulated 500 flights operating in the domestic route, and I reported the percentage change induced by the introduction of the upgrade option. The overall change considers the percentage difference in $t = 0$ prices arising from the introduction of the upgrade option when the airline faces capacity constraints, thus $\Delta p = \frac{p^u - p^{NOu}}{p^{NOu}}$, where p^u is the price when the upgrade option is available, whereas p^{NOu} is the price when the upgrade option is not available. Columns under "change due to SPD" indicate the percentage change due to the introduction of the upgrade option when the airline does not face capacity constraints and thus associated to the use of upgrades as a sequential price discrimination (SPD) tool. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. Bootstrapped standard errors over 20 samples are recorded.

Tables 29, 30, 31, 32 and 33 show the effects of the introduction of the upgrade option for $t = 1$ prices, sales and sellouts on small aircraft flying over the domestic route. Results align with those for large aircraft flying over the international route in Tables 8, 9, 10, 21 and 22.

Table 29: Leisure type demand shock and the effect of introducing upgrades on prices - small aircraft over the domestic route

Demand shock	Change in $p_{1,EC}$
H,H	0.011
	(0.040)
H,M	-0.003
	(0.020)
M,H	0.018
	(0.021)
H,L	-0.002
	(0.044)
L,H	0.026
	(0.051)
M,M	0.002
	(0.009)
M,L	-0.001
	(0.017)
L,M	0.009
	(0.020)
L,L	0.001
	(0.025)

Demand shock	Change in $p_{1,BC}$
H,H	0.138
	(0.091)
H,M	0.076
	(0.038)
M,H	0.050
	(0.033)
H,L	0.021
	(0.048)
L,H	0.042
	(0.052)
M,M	0.066
	(0.016)
M,L	0.042
	(0.023)
L,M	0.046
	(0.035)
L,L	0.041
	(0.056)

Notes: I simulated 500 flights operating in the domestic route under the two scenarios: with and without upgrades. In both cases, the airline faces the same demand shocks and capacity constraints. I evaluate optimal prices for any flight under the two scenarios and then consider their relative difference, in particular the *Change in* $p = \frac{p^U - p^{NoU}}{p^{NoU}}$, with p^U being the scenario with upgrades and p^{NoU} being the scenario without upgrades. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. Bootstrapped standard errors over 20 samples are recorded.

Table 30: Leisure type demand shock and the effect of introducing upgrades on retail sales - small aircraft over the domestic route

Demand Shock	Change in $q_{0,EC}$
H,H	2.343
	(1.340)
H,M	0.817
	(0.636)
M,H	4.898
	(1.959)
H,L	0.023
	(0.480)
L,H	2.313
	(1.607)
M,M	1.764
	(0.663)
M,L	0.118
	(0.330)
L,M	0.218
	(0.214)
L,L	-0.000
	(0.000)

Demand Shock	Change in $q_{0,BC}$
H,H	-1.341
	(0.711)
H,M	-1.358
	(0.398)
M,H	-2.586
	(0.573)
H,L	-0.021
	(0.071)
L,H	-0.307
	(0.241)
M,M	-0.980
	(0.202)
M,L	-0.024
	(0.050)
L,M	0.000
	(0.000)
L,L	0.000
	(0.000)

Demand Shock	Change in $q_{1,EC}$
H,H	0.237
	(0.548)
H,M	0.270
	(0.235)
M,H	-0.007
	(0.282)
H,L	0.196
	(0.431)
L,H	-0.128
	(0.394)
M,M	0.219
	(0.116)
M,L	0.209
	(0.194)
L,M	0.130
	(0.188)
L,L	0.115
	(0.332)

Demand Shock	Change in $q_{1,BC}$
H,H	-0.279
	(0.274)
H,M	-0.128
	(0.154)
M,H	0.039
	(0.267)
H,L	-0.080
	(0.284)
L,H	0.020
	(0.187)
M,M	-0.161
	(0.105)
M,L	-0.128
	(0.151)
L,M	-0.093
	(0.152)
L,L	-0.033
	(0.264)

Notes: I simulated 500 flights operating in the domestic route under the two scenarios: with and without upgrades. In any scenarios, the airline faces the same demand shocks. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. I evaluate retail sales for any flight under the two scenarios and then consider their difference, in particular *Change in* $q = q^U - q^{NoU}$. Bootstrapped standard errors over 20 samples are recorded.

Table 31: Leisure type demand shock and the effect of introducing upgrades on sellouts - small aircraft over the domestic route

Demand Shock	Change in $sellout_{0,EC}$	Demand Shock	Change in $sellout_{0,BC}$
H,H	0.00781	H,H	-0.10278
	(0.02034)		(0.05829)
H,M	0.00000	H,M	-0.08073
	(0.00000)		(0.04807)
M,H	0.00000	M,H	-0.13829
	(0.00000)		(0.03135)
H,L	0.00000	H,L	0.00000
	(0.00000)		(0.00000)
L,H	0.00000	L,H	0.00000
	(0.00000)		(0.00000)
M,M	0.00024	M,M	-0.03197
	(0.00108)		(0.00969)
M,L	0.00000	M,L	0.00000
	(0.00000)		(0.00000)
L,M	0.00000	L,M	0.00000
	(0.00000)		(0.00000)
L,L	0.00000	L,L	0.00000
	(0.00000)		(0.00000)

Demand Shock	Change in $sellout_{1,EC}$	Demand Shock	Change in $sellout_{1,BC}$
H,H	-0.00574	H,H	0.18410
	(0.03102)		(0.08090)
H,M	-0.00829	H,M	0.17803
	(0.01130)		(0.06451)
M,H	0.00000	M,H	0.04519
	(0.00000)		(0.05242)
H,L	-0.04520	H,L	0.05660
	(0.05046)		(0.03717)
L,H	0.00000	L,H	0.00870
	(0.00000)		(0.02517)
M,M	-0.00026	M,M	0.11107
	(0.00118)		(0.02889)
M,L	0.00000	M,L	0.01086
	(0.00000)		(0.01523)
L,M	0.00000	L,M	0.01111
	(0.00000)		(0.01115)
L,L	0.00000	L,L	0.00955
	(0.00000)		(0.01999)

Notes: I simulated 500 flights operating in the domestic route under the two scenarios: with and without upgrades. In any scenarios, the airline faces the same demand shocks. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realizaiton of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. I evaluate the fraction (over the 500 simulations) of flights that sellout; in particular $\textit{Change in sellout}_k = sellout_k^U - sellout_k^{NoU}$, with $sellout_k^U$ being the fraction of flights which sellouts in cabin k in the scenario with the upgrade option, and $sellout_k^{NoU}$ being the fraction of flights which sellout in cabin k in the scenario without the upgrade option. Bootstrapped standard errors over 20 samples are recorded.

Table 32: Leisure type demand shock and upgrades - small aircraft over the domestic route

Demand Shock	Average p_{UP}
H,H	385.8
	(26.417)
H,M	260.0
	(14.105)
M,H	275.6
	(13.978)
H,L	141.9
	(15.661)
L,H	173.6
	(22.838)
M,M	181.9
	(6.478)
M,L	172.7
	(15.421)
L,M	167.2
	(18.929)
L,L	191.7
	(30.638)

Demand Shock	Average q_{UP}
H,H	3.1
	(0.625)
H,M	3.5
	(0.252)
M,H	3.6
	(0.230)
H,L	3.4
	(0.475)
L,H	2.7
	(0.592)
M,M	4.2
	(0.234)
M,L	2.7
	(0.224)
L,M	2.1
	(0.297)
L,L	1.3
	(0.279)

Notes: I simulated 500 flights operating in the domestic route under the scenario with upgrades. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. I evaluate the optimal upgrade price and corresponding realized upgrade sales. Bootstrapped standard errors over 20 samples are recorded.

Table 33: Leisure type demand shock and surplus - small aircraft over the domestic route

Demand Shock	Change in PS
H,H	709
	(562.154)
H,M	558
	(189.943)
M,H	117
	(238.668)
H,L	267
	(109.010)
L,H	510
	(125.451)
M,M	381
	(60.948)
M,L	284
	(57.854)
L,M	253
	(44.803)
L,L	173
	(79.297)

Demand Shock	Change in CS
H,H	1,000
	(737.058)
H,M	234
	(206.631)
M,H	537
	(496.190)
H,L	241
	(179.311)
L,H	491
	(197.730)
M,M	440
	(176.876)
M,L	194
	(81.951)
L,M	184
	(49.300)
L,L	108
	(69.081)

Notes: I simulated 500 flights operating in the domestic route under the scenarios with and without upgrades. Demand shocks are the $t = 0$ leisure type demand shocks, in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$, where H represents a realization of the random coefficient in top 20% of its distribution, L a realization in the bottom 20% and M in the rest. I evaluate surplus in both scenarios and take the difference, for example *Change in* $PS = PS^U - PS^{NoU}$, with PS^U is the producer surplus in the scenario with the upgrade option and PS^{NoU} is the producer surplus in the scenario without it. Bootstrapped standard errors over 20 samples are recorded.

Aggregate welfare effects of the upgrade option

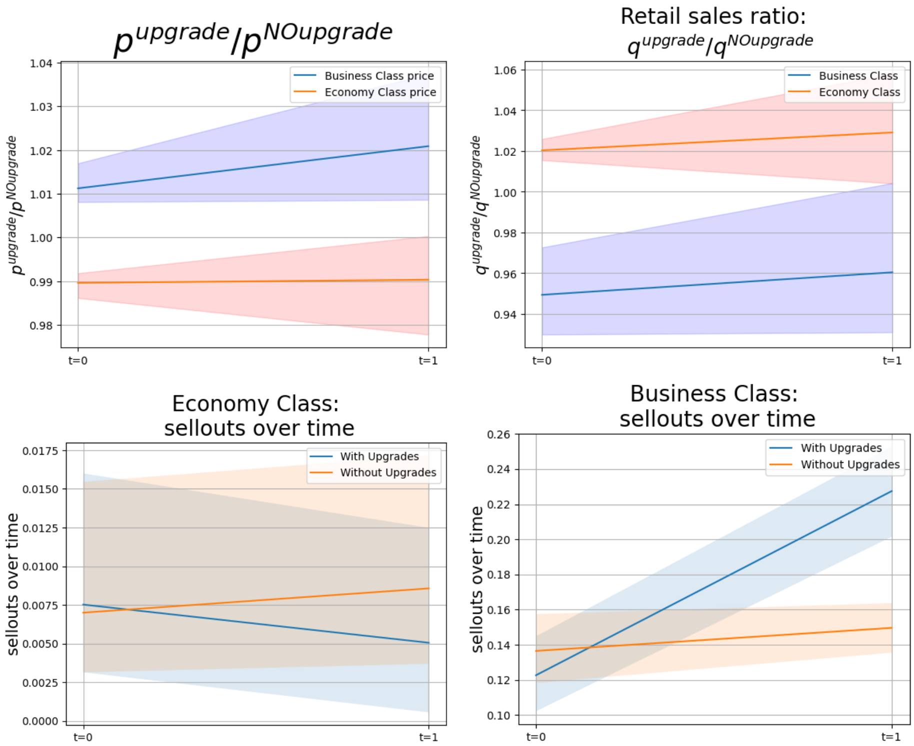
Table 34 compares the average effect of the upgrade option in terms of welfare. Then, I analyze upgrades' effects over time and present them in Figure 16. Results are similar to Table 11 and Figure 7.

Table 34: Counterfactual in levels - small aircraft over the domestic route

	With Upgrades	Without upgrades	$\Delta = With - Without$ upgrades
$p_{EC,0}$	287	289	-2
	(4.35)	(3.9)	(1.08)
$p_{EC,1}$	401	406	-5
	(5.8)	(6.25)	(2.58)
$p_{BC,0}$	955	919	36
	(9.46)	(10.53)	(3.58)
$p_{BC,1}$	805	785	20
	(10.08)	(7.71)	(9.42)
p_{UP}	204		
	(124)		
$passengers_{EC}$	88.35	90.02	-1.672
	(1.72)	(1.67)	(0.35)
$passengers_{BC}$	9.45	7.09	2.365
	(0.22)	(0.27)	(0.15)
upgrades	3.34		
	(0.11)		
$sellout_{EC}$	0.0	0.01	-0.0
	(0.002)	(0.004)	(0.003)
$sellout_{BC}$	0.201	0.122	0.079
	(0.019)	(0.014)	(0.017)
CS	31,274	30,919	355
	(1,157)	(1,157)	(100)
PS	32,319	31,968	351
	(940)	(942)	(60)
TS	63,594	62,887	706
	(2,076)	(2,077)	(124)

Notes: I evaluated the estimates and bootstrap standard errors for large aircraft over the international route. I used 20 bootstrap samples, each simulating 500 aircraft. The variable $passengers_k$ indicates the number of passengers flying in cabin k. The variable $sellouts_k$ indicates the fraction of flights (over the 500 simulated flights) that sellout in cabin k. **CS**, **PS** and **TS** indicate average (per flight) consumer, producer and total surplus respectively.

Figure 16: Counterfactual over time - small aircraft over the domestic route



Notes: I evaluated the estimates and bootstrap 95% confidence interval for large aircraft over the international route. I used 20 bootstrap samples, each simulating 500 aircraft.

Distributional welfare effects of the upgrade option

Tables 35, 36 and 37 show how customers' behavior and welfare change according to the new pricing decisions arising from the introduction of the upgrade option. Results align with those over the international route reported in Section 5.2.

Table 35: Counterfactual, change in the absolute number of retail sales - small aircraft over the domestic route

		Without Upgrades			
	Eliminating upgrades...	Outside Option	*EC*	*BC*	*total*
With Upgrades	Outside Option	114,814	478	15	115,307
		(1,044)	(113)	(4)	(1043)
	EC	804	42,756	570	44,130
		(138)	(818)	(75)	(862)
	$EC + UP$	14	1,598	50	1,662
		(3)	(50)	(8)	(53)
	BC	41	110	2,897	3,048
		(12)	(20)	(107)	(113)
	total	115,673	44,942	3,532	
		(995)	(837)	(138)	

Notes: I evaluated the estimates and bootstrap 95% confidence interval for large aircraft over the international route. I used 15 bootstrap samples, each simulating 500 aircraft.

Table 36: Counterfactual, change of retail sales as percentage of original purchases - small aircraft over the domestic route

		Without Upgrades		
	Eliminating upgrades...	Outside Option	*EC*	*BC*
With Upgrades	Outside Option	99.6%	0.4%	0.0%
		(0.1)	(0.1)	(0.0)
	EC	1.8%	96.8%	1.3%
		(0.3)	(0.4)	(0.2)
	$EC + UP$	0.8%	96.1%	3.0%
		(0.2)	(0.5)	(0.5)
	BC	1.4%	3.6%	95.0%
		(0.4)	(0.6)	(0.8)

Notes: I evaluated the estimates and bootstrap 95% confidence interval for large aircraft over the international route. I used 15 bootstrap samples, each simulating 500 aircraft.

Table 37: Counterfactual, consumer surplus net effects - small aircraft over the domestic route

Eliminating Upgrades $\nearrow$	Outside Option	*EC*	*BC*
Outside Option	0	-17,073	-1,366
	(0)	(4,929)	(876)
EC	57,163	36,743	-40,394
	(14,443)	(38,522)	(10,247)
$EC + UP$	1,443	132,920	9,537
	(663)	(4,550)	(2,176)
BC	47,135	1,589	-50,081
	(17,723)	(2,389)	(10,026)

Notes: I simulated 500 flights under the scenarios: with and without upgrades for 15 bootstrap samples. I reported bootstrap estimates and standard errors. I evaluate consumer surplus for any passenger under the two scenarios and then consider their difference: $CS^{\text{scenario with upgrades}} - CS^{\text{scenario without upgrades}}$. Results are in $.

Tables 38 and 39 show how the introduction of upgrades reduces Business Class retail sales, while at the same time increasing total revenues, thanks to an increase in revenues from Economy Class and upgrade fees. Results are similar to those discussed in Section 5.2.

Table 38: Producer surplus counterfactual, aggregate revenues across cabins - small aircraft over the domestic route

Cabin	With Upgrades	Without upgrades	Δ
EC	26.768$	26.357$	+411$
	(0.734)	(0.725)	(62)
BC	4.977$	5.612$	-635$
	(0.248)	(0.268)	(103)
UP	575$	0$	+575$
	(20)	0	
total	32.320$	31.969$	+351$
	(0.917)	(0.919)	(59.0)

Notes: I simulated 500 flights, within 15 bootstrap samples, under the two scenarios: with and without upgrades. In both cases, the airline faces the same demand shocks. I evaluate consumer surplus for any passenger under the two scenarios and then consider their difference.

Table 39: Producer surplus counterfactual, distribution of revenues across cabins - small aircraft over the domestic route

Cabin	With Upgrades	Without upgrades
EC	0.828	0.825
	(0.005)	(0.005)
BC	0.154	0.175
	(0.005)	(0.005)
UP	0.018	0
	(0.001)	(0)

Notes: I simulated 500 flights, within 15 bootstrap samples, under the two scenarios: with and without upgrades. In both cases, the airline faces the same demand shocks. I evaluate consumer surplus for any passenger under the two scenarios and then consider their difference.

Comparison across aircraft sizes

Table 40 compares percentage changes in relevant outcomes resulting from the introduction of the upgrade option across aircraft with different levels of capacity. The upgrade option has similar effects across aircraft of different sizes. However, in terms of producer surplus, the upgrade option generates more revenues on large aircraft. The main reason of this difference is that when there is a small demand shock along the domestic route, the airline does not use the upgrade option to sequentially price discriminate $t = 0$ travelers, as shown in Table 28. With respect to the international route, two facts explain this result. On one hand, with respect to travelers along the international route, domestic travelers have lower value for comfort. On the other hand, the price of Economy Class and of an upgrade are similar across different routes. Therefore, when there is a low realization of demand, the share of Economy Class ticket holders at the margin for Business Class is so small that the airline does not have an incentive to modify its pricing strategy to sequentially price discriminate.

Table 40: Counterfactual - comparison across different aircraft

	$\%\Delta = \frac{X^{\text{With Upgrades}} - X^{\text{Without upgrades}}}{X^{\text{Without Upgrades}}}$	
Outcome	Small Aircraft	Large Aircraft
$p_{EC,0}$	-0.007	-0.016
	(0.0)	(0.0)
$p_{EC,1}$	-0.012	-0.009
	(0.01)	(0.01)
$p_{BC,0}$	0.039	0.029
	(0.0)	(0.0)
$p_{BC,1}$	0.024	0.013
	(0.01)	(0.01)
$passengers_{EC}$	-0.019	-0.016
	(0.0039)	(0.0028)
$passengers_{BC}$	0.334	0.23
	(0.0332)	(0.0114)
*fraction of upgrading passengers**	0.05	0.05
	(0.0045)	(0.0023)
$sellout_{EC}$	-0.478	-0.7482
	(0.4438)	(0.136)
$sellout_{BC}$	0.6582	0.7453
	(0.1818)	(0.1593)
CS	0.012	0.015
	(0.002)	(0.002)
PS	0.011	0.020
	(0.002)	(0.002)
TS	0.011	0.017
	(0.001)	(0.002)

Notes: I evaluated the percentage change of introducing the upgrade option for small and large aircraft over 500 flights. For example, the variable $sellouts_k$ considers the percentage change - due to the introduction of the upgrade option - of the fraction of sellouts in cabin k. Row * considers the fraction of customers in Economy Class in $t = 0$ who upgrade to Business Class. Bootstrapped standard errors over 10 samples are recorded.

A.10 Appendix - counterfactual: the role of capacity constraints

In this section, to understand how the upgrade option functions, I consider the interaction between the upgrade option and capacity constraints, following the discussion of 5.1. Without capacity constraints, the upgrade option works as a way to sequential price discriminate $t = 0$ customers. With capacity constraints upgrades also serve as a way to manage inventory. To support my claims, firstly, I show the the effect of the introduction of the upgrade option on average across all simulated flights, then I show how results change based on demand shocks.

A.10.1 Appendix - counterfactual: no capacity constraints

In this section, I examine the role of upgrades in the absence of capacity constraints on average across all flights. When there are no capacity constraints, upgrades serve as a tool to sequential price discriminate $t = 0$ customers, which affects $t = 0$ prices.

In the absence of capacity constraints, introducing upgrades leads to an increase in Business Class prices and a decrease in Economy Class prices in $t = 0$, with no impact on $t = 1$ prices. The pricing decisions in one period do not affect the decisions in the other period. This happens because the intertemporal connection between prices lies in the evolution of capacity over time, but in this scenario there are no capacity constraints. In this scenario, upgrades serve as a tool for sequential price discrimination, allowing the airline to implement second-degree price discrimination twice. In period $t = 0$, it screens all customers between higher and lower quality products, then, in period $t = 1$, it sorts lower quality product holders between those who choose to upgrade and those who do not. The effects of the upgrade option on $t = 0$ prices are similar to the effects of introducing an intermediate quality good between Economy and Business Class in period $t = 0$. This concept is similar to the idea of "versioning" discussed by Varian (1989), where different versions of a product are offered at different prices to target different segments of customers. Similarly for welfare, as shown in Table 41 the upgrade option increases the number of travelers flying and increases total welfare for both customers and travelers.

Table 41: Counterfactual, role of capacity constraints - large aircraft over the international route

	WITH capacity constraints		WITHOUT capacity constraints	
	With Upgrades (1)	Without Upgrades (2)	With Upgrades (3)	Without Upgrades (4)
$p_{EC,0}$	303	308	313	317
	(3.33)	(2.95)	(2.95)	(2.49)
$p_{EC,1}$	418	422	430	430
	(5.29)	(5.64)	(5.28)	(5.28)
$p_{BC,0}$	1305	1268	1,152	1,134
	(12.77)	(11.32)	(14.23)	(11.96)
$p_{BC,1}$	996	983	848	848
	(13.92)	(24.15)	(15.61)	(15.61)
p_{UP}	297		268	
	(134)		(115)	
$passengers_{EC}$	164.5	167.2	145.69	150.27
	(2.85)	(3.24)	(2.25)	(2.82)
$passengers_{BC}$	29.3	23.82	42.36	35.13
	(0.86)	(0.83)	(1.73)	(1.61)
upgrades	7.11		7.78	
	(0.19)		(0.25)	
$sellout_{EC}$	0.01	0.03	0	0
	(0.004)	(0.009)	(0.0)	(0.0)
$sellout_{BC}$	0.166	0.096	0	0
	(0.016)	(0.015)	(0.0)	(0.0)
CS	81,978	80,751	87,248	85,897
	(3,017)	(3,049)	(3,655)	(3,675)
PS	80,451	78,897	84,414	82,536
	(2,251)	(2,214)	(2,587)	(2,558)
TS	162,430	159,649	171,663	168,434
	(5,244)	(5,239)	(6,216)	(6,211)

Notes: I evaluated the estimates and bootstrap standard errors for large aircraft over the international route. I used 10 bootstrap samples, each simulating 500 aircraft. The variable $passengers_k$ indicates the number of passengers flying in cabin k. The variable $sellouts_k$ indicates the fraction of flights (over the 500 simulated flights) that sellout in cabin k. **CS**, **PS** and **TS** indicate average (per flight) consumer, producer and total surplus respectively.

A.10.2 Demand shock without capacity constraints

In this section, I complement the evidence on the consequences of the upgrade option without capacity constraints based on the demand shock of Table 7. I consider the effects of the upgrade option on retail sales and upgrades. Results are similar to those in Tables

9: as an effect of the price differences induced by upgrades there are substitutions effects across different cabins. Moreover, as demand shocks increase, upgrade prices increase together with the number of upgrade sales.

Table 42: Leisure type demand shock and retail sales changes - large aircraft over the international route

Demand shock	Change in $q_{0,EC}$
H,H	2.798
	(1.039)
H,M	0.938
	(0.888)
M,H	7.646
	(3.114)
H,L	-0.083
	(0.182)
L,H	22.547
	(6.877)
M,M	2.251
	(0.995)
M,L	2.790
	(1.284)
L,M	1.482
	(1.805)
L,L	-1.093
	(1.441)

Demand shock	Change in $q_{0,BC}$
H,H	-3.684
	(1.572)
H,M	-0.461
	(0.612)
M,H	-1.494
	(0.666)
H,L	-0.030
	(0.066)
L,H	-1.956
	(0.783)
M,M	-0.170
	(0.086)
M,L	-0.209
	(0.124)
L,M	-0.267
	(0.143)
L,L	-0.052
	(0.074)

Notes: I simulated 500 flights operating in the international route under the two scenarios without capacity constraints: with and without upgrades. In both cases, the airline faces the same demand shocks. I evaluate optimal prices for any flight under the two scenarios and then consider their difference. Change is measured as $x^U - x^{NoU}$. Results are in \$ and demand shocks are in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$. Bootstrapped standard errors are recorded.

Table 43: Leisure type demand shock and upgrades - large aircraft over the international route

Demand shock	p_{UP}
H,H	355.404
	(22.339)
H,M	282.196
	(11.118)
M,H	334.264
	(10.015)
H,L	191.543
	(26.889)
L,H	299.346
	(30.034)
M,M	267.218
	(7.772)
M,L	209.548
	(22.396)
L,M	259.447
	(13.379)
L,L	253.358
	(38.295)

Demand shock	q_{UP}
H,H	8.994
	(1.190)
H,M	11.199
	(0.401)
M,H	6.944
	(0.269)
H,L	9.272
	(1.699)
L,H	6.385
	(0.852)
M,M	8.594
	(0.346)
M,L	6.304
	(0.623)
L,M	5.484
	(0.609)
L,L	3.619
	(0.537)

Notes: I simulated 500 flights operating in the international route under the scenario without capacity constraints. I evaluate optimal upgrade prices for any flight and then simulate the corresponding demand for upgrades. Results are in $ and demand shocks are in the form of $\beta_{leisure,0}, \gamma_{leisure,0}$. Bootstrapped standard errors are recorded.