PRICING DYNAMICS AND SCREENING MECHANISMS

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ABSTRACT

Garrett Scott: Pricing Dynamics and Screening Mechanisms
(Under the direction of Fei Li and Jonathan Williams)

Uncertainty and risk aversion play an important role in consumer decision making in many settings. Using novel proprietary data from an airline that includes passenger-level bookings and cancellations, I study the effectiveness of screening by airlines on consumer uncertainty using a menu of refunds. I find that cancellation rates of tickets range from 4.58% to 14.44% across flight segments, associated fees make up 1.54% of the airline's revenue on these segments, and tickets without refunds are cancelled least often. To study the welfare implications of alternative refund strategies, I develop and estimate a model in which consumers face dynamic prices and make purchase decisions over tickets differentiated by quality and cancellation fees. I find that strategies that provide greater flexibility to consumers reduce profits more than the increase in consumer welfare.

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1.1 Introduction

Consumers often face uncertainty at the time of their purchase. In particular, the uncertainty of whether a consumer will ultimately need or use a good plays a significant role in many markets. Studies have shown that more than 5% of event tickets are resold below face value on websites such as StubHub (Leslie and Sorensen (2014); Vollmer (2021)); industry reports reveal that the global average of hotel cancellations reached as high as 40% in recent years[1]; and I find that 12% of airline tickets are canceled before departure. Although these mechanisms differ in practice, each serves the purpose of insuring consumers against demand shocks and reducing the inefficiencies created by the initial misallocation. The choice of mechanism depends on the industry, but unlike resale, refunds provide the seller the opportunity to screen consumers on their uncertainty in addition to their willingness to pay while taking on the burden of insurance and reallocation. In general, price discrimination can have an ambiguous effect on welfare, but the welfare implications of screening on uncertainty and willingness to pay are relatively unknown.

This paper evaluates the welfare implications of screening uncertain consumers with a menu of tickets vertically differentiated in quality and refundability. To study this question, I develop a model in which consumers choose from a menu of time-varying fares differentiated by quality and cancellation fees. Using novel proprietary data from a North American airline that include information on bookings, cancellations, and aircraft seat inventories, I perform a descriptive analysis and estimate the structural model. The model estimates provide a distribution of consumer heterogeneity in valuations, uncertainty, and risk aversion that is used to evaluate counterfactual

[1] "Global Cancellation Rate of Hotel Reservations Reaches 40% on Average." *Hospitality Technology.*

refund policies. I find that strategies that provide greater flexibility to consumers reduce profits more than the increase in consumer welfare.

The data used in the study come from a North American airline and combine details on the booking and cancellation decisions of consumers and aircraft seat inventories. The primary data contain consumer transactions from January 1^{st}, 2019 to December 31^{st} 2019. The transactions are recorded at the passenger-flight level and consist of both bookings and cancellations. In the data, I am able to observe the timing of purchase and cancellation, ticket selection, and transaction price for all consumers who purchase. The sample used in the analysis contains nearly $200,000$ consumer itineraries for a subset of flights connecting more than a dozen cities. I supplement this data with cabin-level seat inventory measurements that capture the set of tickets available to consumers on each day leading up to every flight. Together, the transaction prices and inventory measurements detail the dynamic menu that the airline offers to consumers.

The airline offers three ticket classes in the Economy cabin that are vertically differentiated in quality and cancellation fee; higher class tickets have greater quality and smaller fees. The bundling of higher quality and reduced cancellation fees is a common practice in the airline industry. Seven of the nine largest North American airlines provide similar menus of tickets.

In the descriptive analysis, I observe a great deal of heterogeneity in the timing of purchase and ticket selection of consumers. There is also evidence that the decisions of consumers are influenced by the airline's revenue management practices, as the cheapest tickets are purchased far in advance of the flight. The transaction data reveal that 12.15% of itineraries are canceled, and cancellation fees make up 2.69% of the airline's revenue. Of the three ticket classes, the lowest, which is not refundable, is canceled the least frequently.

Consumers who book with the airline face a complex decision. The airline offers a menu of tickets, each with a unique set of quality attributes and a pre-determined cancellation fee. The airline adjusts the menu by increasing or decreasing prices, or even completely removing ticket options. Because of the nature of the environment, consumers must evaluate their utility along multiple dimensions, including uncertainty. Thus, consumers must choose between purchasing one of the available tickets today and delaying purchase until the future when the menu may be less favorable.

I propose a structural model that characterizes the consumer's decision process. In the model, there are t discrete periods in which consumers heterogeneous in valuations and risk aversion can purchase tickets. In a given period, a consumer decides whether to buy a ticket in one of the available fare classes based on rational expectations of future prices and demand shocks. Similar to Leslie and Sorensen (2014) and Vollmer (2021), these shocks lead consumers to cancel their ticket and can arrive in any period following the purchase. The solution to the model provides insight into the role that differences in preferences, specifically valuations and risk aversion, have in determining the timing and type of purchase made by consumers.

In an approach similar to Fox et al. (2016), Nevo et al. (2016), and Aryal et al. (2021), I estimate the model in two stages. In the first stage, I recover a price process, conditional on market characteristics, that characterizes the dynamic menu. Variation in the price processes across markets captures the differences in risk that consumers face from price volatility and sell outs. I then construct a set of moments from the data that capture the timing and type of purchases and the rate of cancellations. In the second stage, I solve the model for a variety of candidate consumer types that differ in valuations, risk aversion, and uncertainty. For each of the candidate types, I construct the analogous moments to those calculated from the data. The estimation approach then weights the candidate types to identify a mixture of types that best matches the empirical moments. The estimation procedure is flexible in that it requires no assumptions about the distribution of model parameters, and I find substantial heterogeneity along the different dimensions both within and across markets.

I use the model estimates to consider the welfare implications of alternative refund policies given the revenue management system that dictates prices. The regulation of refund policies in the airline industry falls on the U.S. Department of Transportation (DoT), which requires airlines to refund all cancellations within twenty-four hours of booking for purchases made at least seven days before departure or hold a price for a consumer for twenty-four hours.

In the first counterfactual, I remove the DoT's regulation and allow the cancellation fee to be dictated by the airline's policy. I find that the removal of the regulation leads to fewer purchases and a reduction in consumer surplus, but an increase in sales of the most expensive refundable tickets and a larger sum of cancellation fees results in higher revenues for the airline. Overall, the DoT policy facilitates purchases and improves consumer surplus and total welfare. In a second counterfactual, I explore a policy that offers even greater protection for the middle ticket class via a less rigid cancellation fee schedule. The proposed change decreases profit and total surplus but increases consumer surplus. This policy has an additional effect in that induces consumers that might otherwise not buy to purchase.

The remainder of the introduction discusses the related literature. Section 2 presents the data sources and the relevant institutional details, and Section 3 provides descriptive evidence. Section 4 presents the structural model, and Section 5 provides details of the estimation. Section 6 presents the results of the estimation and discusses the counterfactual experiments and their results. Section 7 concludes.

1.1.1 Related Literature

This paper contributes to several areas of the literature, including refunds, demand uncertainty, and price discrimination. Overall, this analysis improves the broader understanding of markets that feature refunds and screening on uncertainty. Despite many potential refund policies, little empirical research has been done to evaluate their performance and the factors that affect them. Previous theoretical work has relied on strong assumptions regarding the correlation of consumer valuations, uncertainty, and time of uncertainty resolution in analytically finding conditions under which sequential screening is optimal for the firm. However, the difference in efficiency of these various policies remains unclear, especially in more general settings. Therefore, the implications of this paper reach far beyond air travel to a broader range of perishable goods markets, including those in the tourism industry and the numerous retail markets that utilize refunds.

The literature on refund contracts is relatively nascent, but refund contracts have analytically been shown to be profit-maximizing under many conditions and in a variety of settings. Courty and Li (2000) show that when consumers are aware of only their type-specific distribution of valuations at the time of contracting, an airline optimally offers a larger refund contract to consumers with greater valuation uncertainty and a less expensive, low refund contract to more certain consumers. A similar study is that of Akan et al. (2015) in which all consumers become aware of their type prior to contracting but learn their valuation at different times leading up to the shared consumption date. Here, an optimal menu is one that differs in the amount of the refund and the deadline at which the refund can be exercised. In a related paper, Escobari and Jindapon (2014) show that as the individual uncertainty of all consumers is resolved over time, the prices of two tickets that differ only in their refund amount optimally converge as the departure date nears. They provide empirical evidence using data on airline ticket prices to support this claim.

Refunds also seek attention in experience goods environments where consumers do not learn about product fit until after purchasing the good. Hinnosaar and Kawai (2020) show that guaranteed profit in the experience goods setting can be maximized with a combination of large refunds and non-refundable random discounts. This work also relates to the Xie and Gerstner (2007) study of service cancellation fees, which finds that allowing for cancellations can be profit-maximizing for a capacity-constrained service when consumers receive idiosyncratic preference shocks. Likewise, Che (1996) focuses on return policies as insurance for risk-averse consumers and shows these can be optimal when consumers are highly risk-averse or retail costs are high.

There are many similarities between refunds and resale markets, as both allow for reallocation to consumers with higher valuations. In a closely related paper, Vollmer (2021) uses primary and secondary market transactions for college football tickets to estimate the welfare effects of resale markets. In a counterfactual analysis, they find that a menu of refunds with options for different states of the world improves profit relative to a no-reallocation policy but leaves consumer welfare unchanged. Other empirical studies of ticket resale markets include Sweeting (2012), Leslie and Sorensen (2014), and Waisman (2021). Similarly, Lazarev (2013) aims to estimate the welfare effects of resale, refunds and reallocation when airline passengers learn about travel conflicts after purchasing a ticket. Cancellations are not directly observed, and changes in prices are used to estimate the probability of a cancellation.

This paper also relates to the literature on demand uncertainty, as the use for refunds arises from the uncertainty that both sides of the market face at the time of purchase. In particular, there are many studies of how firms and consumers optimize when agents resolve uncertainty over time. Bergemann and Välimäki (2019) provide an overview on the dynamic mechanism design literature, including a discussion on sequential screening mechanisms similar to those mentioned previously. Similarly, Ching et al. (2013) provide an overview of the learning literature in which agents resolve uncertainty regarding model primitives over time through information acquisition. In this paper, consumers form an expectation of their valuation that can be adjusted as they receive shocks leading up to departure. All uncertainty is completely resolved on the day of the flight.

There is a literature related to uncertainty that focuses on market inefficiencies due to asymmetric information. The seminal paper in this literature is the Akerlof (1970) study of used car markets. Insurance as a response to such market inefficiencies has been thoroughly considered. Previous studies related to insurance have focused on the effects of competition in insurance markets (Rothschild and Stiglitz (1976); Jaynes (1978); Azevedo and Gottlieb (2017)), selection in insurance markets (Hemenway (1990); de Meza and Webb (2001); Cohen and Einav (2007); Einav et al. (2013)), and estimating the welfare effects of asymmetric information in insurance markets (Einav et al. (2010b); Einav et al. (2010a)). These papers focus on traditional forms of insurance with third-party provision. Insurance in the context of this paper differs in that the insurance provider is the original seller of the good.

An area of the literature has focused on pricing mechanisms used by airlines when facing uncertainty caused by stochastic demand. Dana (1999) shows that airlines optimize by releasing a limited quantity of tickets at multiple price points in advance of departure when demand is uncertain. This is closely related to a set of papers (Dana (1998); Nocke et al. (2011)) detailing the use of advance purchase discounts (APDs) as a price discriminatory tool. APDs incentivize more certain low-value consumers to purchase before prices increase. Empirical papers such as Lazarev (2013), Aryal et al. (2021), and Williams (2021) find evidence that dynamic prices are profit-maximizing when the arrival rate of consumers and composition of consumer types is stochastic.

This paper also compliments the existing literature on revenue management (Talluri and Ryzin (2006); Gale and Holmes (1993); Gallego and van Ryzin (1994); Board and Skrzypacz (2016); Dilmé and Li (2019)). These papers describe optimal pricing mechanisms in settings where capacity and the time horizon to sell are both limited. This paper does not attempt to solve for an optimal pricing mechanism. However, consumers' decisions depend on their expectations of prices and the airline's rationing policy.

Finally, this paper also contributes to the vast literature on price discrimination. Estimating the impact of screening practices on efficiency and the division of welfare has been an area of interest for industrial organization economists. Empirical papers focus mostly on intratemporal price discrimination (Leslie (2004); Crawford and Shum (2007); McManus (2007); Ivaldi and Martimort (1994); Busse and Rysman (2001); Aryal et al. (2021)) or intertemporal price discrimination (Lazarev (2013); Hendel and Nevo (2013); Garrett (2016)). Similar to Aryal et al. (2021) and Chandra (2020), this paper explores the effects screening both on preferences with quality differences and on purchase dates with dynamic prices. This is the first paper to consider screening on quality, date of purchase, and consumer uncertainty.

1.2 Data

1.2.1 Data Sample

The data are obtained from a North American airline that operates domestic and international passenger flights. The primary data contain all consumer purchases from 2018 and 2019 and include a passenger identification code that allows purchases to be matched to cancellations. For each itinerary, I observe the fare paid, ticket class, refund policy, and timing of purchase and cancellation.

I supplement these with a secondary data set, also provided by the airline, containing cabin inventories for all flights during the same time span. The inventory data are collected at the beginning of each day leading up to the flight and track seats sold to date and seats remaining in each cabin. In addition to inventory measurements, each observation includes the number of tickets that the airline had available for purchase in each class at the time of data collection. Flights in the data are identified by a unique combination of departure date, origin airport, destination airport, and flight number, and the inventory data can be matched to the transaction data by these flight identifiers and the data record date.

I use a subset of the data from from 2019 that includes 18 domestic and 10 international directional flight segments, each originating or ending at one of the airline's hub airports. Selection of these segments is not random or trivial. I filter based on the following criteria common to the literature:

1. there is only one airline operating nonstop;
2. there are no nearby alternative airports serving the same origin-destination;
3. the distance between airports is at least 400 miles;
4. the airline provides at most two flights per day;
5. the airline has been operating on the segment for at least one year prior to 2019.

This results in a sample of $11,385$ flights. I retain all of the transactions on the remaining flights for the purpose of constructing the prices processes but choose a subset of itineraries for the descriptive analysis and model estimation. I begin by removing all itineraries with transactions outside of the three standard Economy ticket classes. This includes tickets in the Business and Premium cabins and those with special fares including group tickets, awarded tickets, and tickets purchased with rewards points. In sum, these bookings make up less than 10% of all recorded purchases in 2019, with many flights completely void of certain class transactions. Next, I condense the range of each flight to the final 150 days before departure due to sparseness in the transaction data. Tickets are typically made available at least 300 days before departure, but more than 90% of all bookings occur less than five months in advance of the flight.

Finally, I remove itineraries booked across multiple dates and limit the sample to single flight itineraries and round-trip itineraries with two nonstop flights. This criteria, in addition to the criteria for segment selection, facilitate some of the modeling decisions to come in which I focus on identifying the aspects of consumer demand that influence the choice of ticket for a given flight on a segment and avoid the choice of flight or segment. Following other cuts that ensure I have enough transactions from the remaining flights to estimate a price process for each class, I arrive at a final sample that consists of $168,343$ itineraries from $11,183$ different flights.

1.2.2 Ticket Classes and Cancellation Fees

Within the Economy cabin, the airline offers the three ticket classes presented in Table 1.1.[2] For convenience of exposition, I will refer to the tickets as E1, E2, and E3, respectively. The first three rows of each panel focus on the benefits provided by the ticket. Does the consumer receive rewards points for their miles? Do they have to pay a fee for their first checked bag? Is there a fee for selecting their seat before it is assigned? The final row describes the airline's cancellation policy, to be discussed below. There is one difference between the menus for domestic and international flights. The airline does not enforce a cancellation fee for the domestic E3 ticket, but a fee equivalent to the E2 ticket is charged to consumers who cancel an international E3 ticket.

Table 1.1: Economy Ticket Class Structure

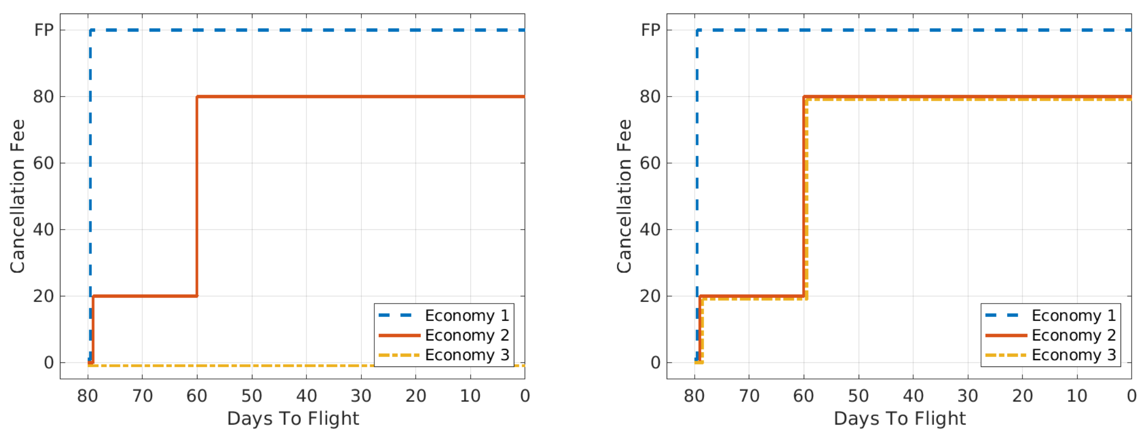
	Economy 1	Economy 2	Economy 3
Rewards Points	No	Yes	Yes
Checked Bag Fee	Yes	Yes	No
Seat Selection Fee	Yes	Yes	No
Cancellation Fee	Yes	Yes	D: No/I: Yes

Note: This table describes the ticket class structure for the airline's Economy cabin and the characteristics that differentiate them. These features include whether the passenger receives rewards points for the purchase, whether the passenger must pay an additional fee for checked baggage or to select a seat in advance, and whether there is a fee for canceling the ticket.

[2] The airline dedicates an entire page on its website to describing the differences in ticket classes and makes them prominently visible at the time of selection. Thus, I assume throughout that consumers are completely aware of ticket characteristics when booking.

Within a market, the tickets are vertically differentiated. Moving from the lowest to highest ticket class, the benefits are increasing and the cancellation fee is (weakly) decreasing. As is common throughout the travel industry, the airline adjusts the fee for canceling as the flight date approaches with a set of deadlines. The first deadline occurs twenty-four hours after booking and satisfies the U.S. Department of Transportation regulation that states airlines are required to allow passengers who purchase at least seven days before the flight's departure the ability to cancel their ticket within a day of purchase and receive a full refund.[3] I refer to this twenty-four hour rule as the "forgiveness period." A second deadline applies only to those passengers who purchase a partially-refundable ticket (domestic E3 and international E2 and E3) more than 60 days before departure. At the deadline of 60 days, the fee, which is a flat rate, quadruples. Figure 1.1 provides an illustrative example of the fee schedule.

Figure 1.1: Cancellation Fee Schedule



(a) Domestic (b) International

Note: The figure displays the cancellation fee schedule a consumer purchasing 80 days before departure faces. The fee depends on the type of segment, the ticket class, and the day of cancellation.

[3]Alternatively, an airline can allow consumers to put a ticket price on hold for twenty-four hours, but many airlines opt for the full refund strategy.

1.3 Descriptive Evidence

In this section, I conduct a preliminary analysis of the data as motivation for the modeling decisions to come. To begin, I survey the airline's revenue management process and explore the effect that the airline's pricing and inventory management strategies have on the consumers' booking decisions. I follow with an investigation into the frequency and timing of cancellations. I provide evidence that cancellations occur with relatively high frequency, and the proportion of cancellations is smaller for tickets with larger cancellation fees.

1.3.1 Pricing and Inventory Management

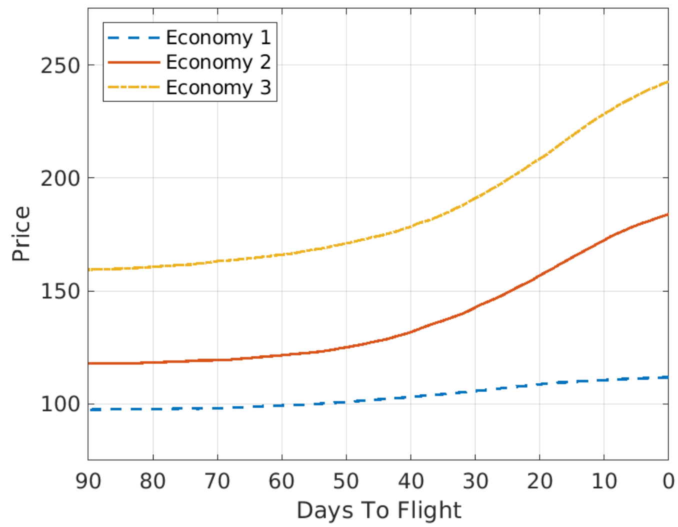
Pricing and inventory management in the context of the airline industry has been well-explored in the literature. Due to obstacles in the data collection of seat inventories, previous empirical studies have focused primarily on dynamic pricing.[4] The literature has provided evidence of significant intratemporal price variation in the industry, with prices on a given flight increasing on average over time. Figure 1.2, which displays the progression of prices in the menu over the final 90 days before departure, supports the primary findings of the literature and additionally demonstrates that prices are increasing across all ticket classes leading up to departure.

In addition to dynamically adjusting prices, airlines remove ticket options over time due to the changing composition of demand preferences and the capacity constraints on airplanes.[5] Figure 1.3 plots the proportion of flights in the sample with the indicated ticket class unavailable to consumers on each day leading up to the flight. In general, all ticket classes are more likely to be removed over time as the number of available seats decreases and the departure date nears. E1 is typically the first ticket class removed, as it is the lowest in value. E3, being the highest in value, is often available as long as there are empty seats in the Economy cabin.

[4]See McAfee and te Velde (2007); Escobari (2012); Lazarev (2013); Aryal and Gabrielli (2020); Williams (2021); Chandra (2020) for studies concerning dynamic airline pricing.

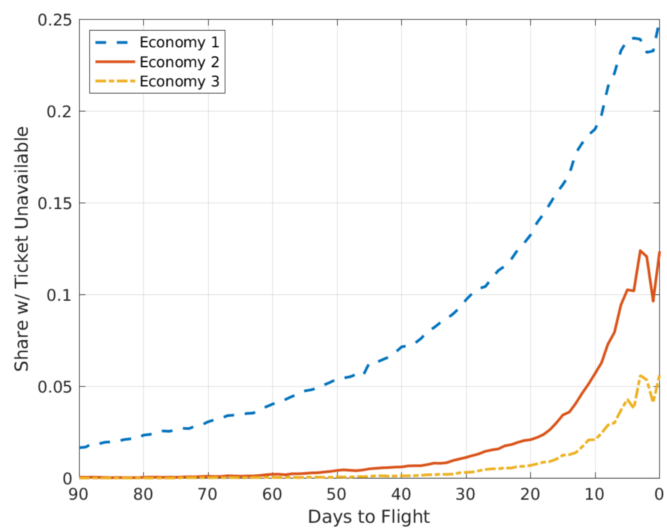
[5]This process is referred to as rationing in the revenue management literature.

Figure 1.2: Dynamic Pricing of Tickets



Note: The figure displays a price path for each ticket class. Flight-specific price paths are created from a kernel regression of transaction prices on purchase date. The plots show the median prices across all flights for each ticket class.

Figure 1.3: Rationing of Tickets

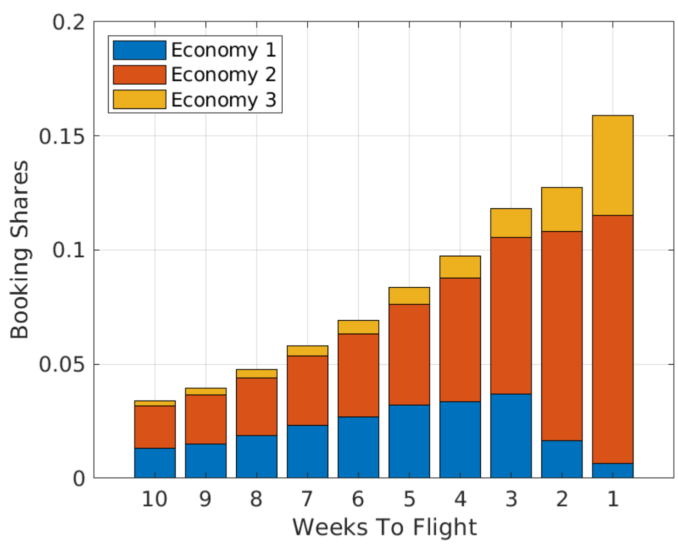


Notes: The figure displays the share of flights with a ticket class unavailable at each day leading up to the flight's departure. Plots are provided for each ticket class.

1.3.2 Bookings

The impact that the airline's revenue management process has on consumer bookings is evident in Figure 1.4, which shows both the shares of all tickets booked across weeks and the shares of bookings for each class within weeks. Due to the nature of round-trip itineraries, I only consider the first flight when examining the timing of bookings and cancellations. Ticket sales as a whole are increasing over time, but the class shares change considerably. Initially, E1 is a popular choice for consumers, but in the final few weeks, the majority of sales are for E2 and E3 tickets. The transition in booking shares corresponds to the removal of classes from the menu illustrated in Figure 1.3. Additionally, as tickets are removed, the airline adjusts prices in response to changes in the composition of demand. As observed in Figure 1.2, the prices of E2 and E3 tickets rise sharply in the final two months as the booking shares of these tickets increase.

Figure 1.4: Bookings by Ticket Class



Notes: The figure displays shares of consumer bookings. First, the figure reveals the distribution of shares of tickets purchased across weeks with the columns summing to one. Within weeks, the figure displays the shares of bookings by ticket class.

Figures 1.2-1.4 together illustrate the intertemporal choice each consumer faces. At any time before departure, a consumer can purchase one of the available ticket classes at the price set by the airline for that day. The consumer also has the choice to delay purchase until a time in the future when they are more certain of travel or expect a lower price. However, they are more likely to observe a menu with higher prices or fewer ticket options in the future. This trade-off characterizes the consumer's optimal stopping problem.

Table 1.2 describes booking patterns in data with itineraries separated by segment type. The ticket selected most often in the sample is E2, most closely followed by E1. The margin between the two booking shares is even smaller when considering the subset of purchases made when all tickets are available.[6] The airline effectively markets the E1 ticket as a product of lower quality. Thus, the premium in price between these two tickets accounts for the quality increase associated with the E2 ticket and the protection offered by the partial cancellation fee. On the other hand, the margin between the booking shares of E2 and E3 tickets is much larger, especially for international flights where the premium in price does not include additional protection from cancellation fees. When consumers are deciding which ticket to purchase, they must weigh the benefits along both dimensions while also factoring in the cost of the ticket. The trade-offs in this decision characterize the consumer's intratemporal problem.

Figure 1.5 provides further insight into the heterogeneity across segments with kernel densities of the segment-specific statistics from Table 1.2. Panel (a) of the figure shows the kernel densities of the booking shares. Economy 2 is frequently chosen across all segments, with booking shares ranging from 40% to 80%. However, the plots of the Economy 1 and Economy 3 booking shares indicate that there are segments in which these tickets are rarely ever chosen. Panel (b) similarly explores the heterogeneity in average segment prices. The shapes of the Economy 1 and Economy 2 densities reveal some variation across segments, but the variation is much less than that in prices for Economy 3 tickets. Additionally, average segment prices of Economy 1 and Economy 2 tickets have a correlation coefficient of 0.9585, while the correlation coefficient of Economy 2 and Economy 3 prices is just 0.6209. This finding indicates a great deal of heterogeneity across segments in the right tail of consumer willingness to pay.

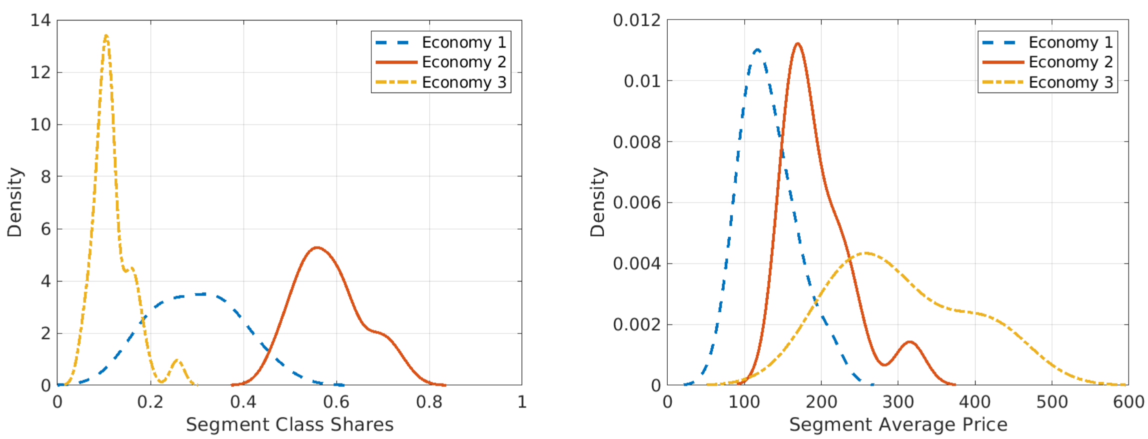
[6]For additional statistics regarding the itineraries, see Appendix A.0.1.

Table 1.2: Booking Descriptives

	Sample	Economy 1	Economy 2	Economy 3
Domestic				
Booking Shares	66.50%	29.22%	57.04%	13.74%
Transaction Price				
Mean		\$134.68	\$197.42	\$265.74
SD		\$45.81	\$80.47	\$103.74
Advance Purchase Days				
Mean		46.5	28.0	21.6
SD		30.1	27.8	25.8
International				
Booking Shares	33.50%	26.57%	64.70%	8.73%
Transaction Price				
Mean		\$119.57	\$184.60	\$362.45
SD		\$53.55	\$90.69	\$180.01
Advance Purchase Days				
Mean		50.0	50.3	30.6
SD		32.6	36.8	32.2

Note: The table provides descriptive statistics on itinerary bookings. The included statistics are the proportion of bookings on each segment type, the proportion of bookings for each ticket class, and the average and standard deviation of the transaction prices.

Figure 1.5: Segment Heterogeneity: Bookings



(a) Booking Shares (b) Average Prices

Notes: The figure displays the heterogeneity across segments in (a) class shares and (b) average prices. The plots are constructed using a kernel density estimation of the statistics from all 28 directional segments.

1.3.3 Cancellations

Of the $168,343$ itineraries in the sample, 7.49% are canceled, and 4.11% are canceled beyond the forgiveness period. In total, the cancellation fees collected by the airline make up 1.54% of the revenue from the consumers in the sample. Table 1.3 provides a brief overview of cancellations by ticket class. It is no surprise that E1 tickets are canceled far less frequently than the other tickets, even during the forgiveness period. Additionally, nearly 1% of all E1 tickets are canceled more than twenty-four hours after booking, though it is worth noting that consumers have no incentive to cancel the ticket beyond the forgiveness period. Further, the table reveals that the proportion of cancellations by ticket class is increasing in both types of segments as the average cancellation fee decreases. Motivated by the findings at the findings at the end of Section 1.3.2, I expolore the potential heterogeneity in cancellations across the nine domestic segments in Figure 1.6

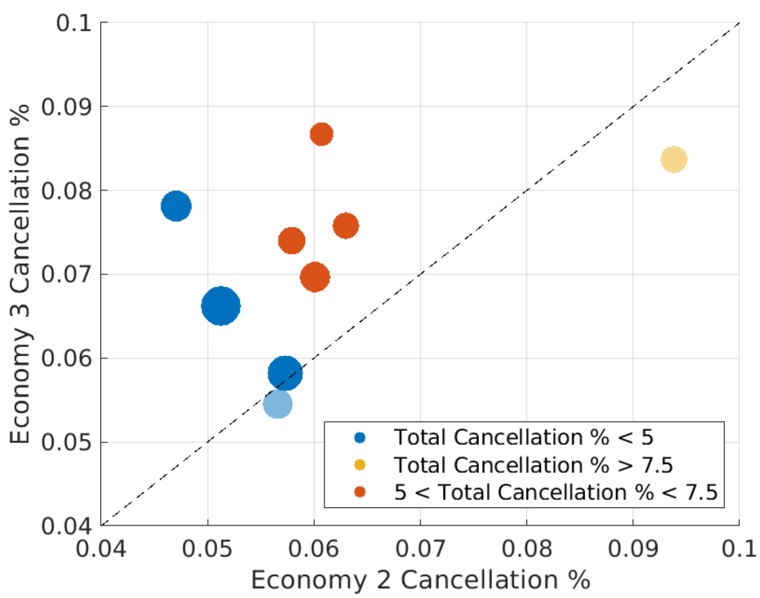
Table 1.3: Cancellation Descriptives

	Economy 1	Economy 2	Economy 3
Domestic			
Cancellation Percentages			
All	3.34%	5.94%	7.09%
After Forgiveness Period	0.99%	3.77%	4.42%
Average Cancellation Fee	\$135.59	\$76.65	\$0
International			
Cancellation Percentages			
All	4.44%	14.45%	14.01%
After Forgiveness Period	1.16%	8.07%	7.88%
Average Cancellation Fee	\$131.70	\$64.22	\$73.35

Note: The table provides descriptive statistics on itinerary cancellations. The included statistics are the proportion of cancellations for each ticket class, the proportion of cancellations that occur after the twenty-four hour forgiveness period, and the average cancellation fee.

Figure 1.6 displays a scatter with each dot corresponding to a domestic segment-specific pair of E2 and E3 cancellation proportions. The size of the dot reveals the proportion of observations from the segment in the final sample, and the color of each dot corresponds to the proportion of cancellations across all ticket classes. Of the nine segments, the seven opaque dots above the 45

Figure 1.6: Segment Heterogeneity: Cancellations



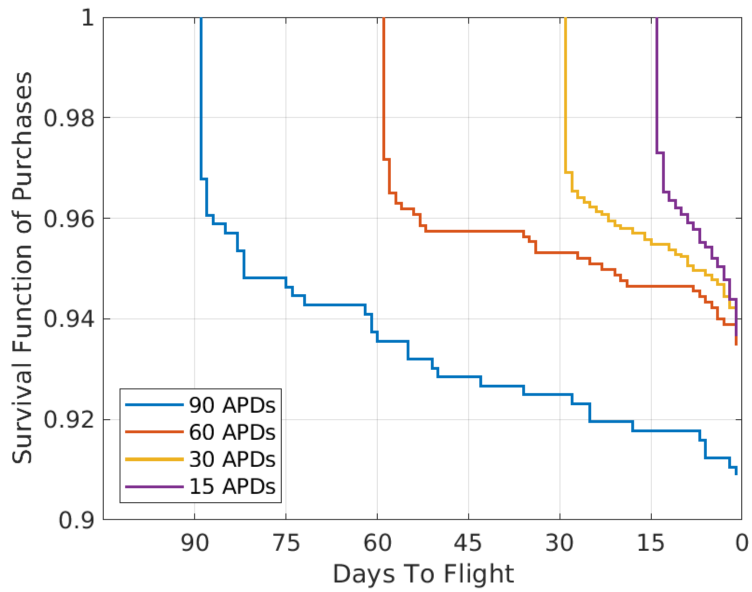
Notes: The figure displays the scatter plot of domestic segment-specific E2 and E3 cancellation proportion pairs. The size of the dot corresponds to the proportion of observations from the segment in the sample. The color of the dot indicates the cancellation proportion across all ticket classes. The opacity of dot indicates the expected relationship between the two proportions: E3 canceled more often than E2.

degree line indicate the expected relationship with E3 canceled more often than E2. However, there are two segments that exhibit a higher cancellation rate of E2 tickets. There are many potential explanations for this finding.[7] However, this indicates the importance of flexibility in estimating the covariation between preferences and uncertainty.

In addition to revealing which tickets are canceled, the data provide insight into the timing of cancellations. These insights indicate parallels between the airline consumers who receive shocks after purchase that lead them to cancel their travel plans and the events studied in survival analysis. Figure 1.7 shows the Kaplan-Meier curve of cancellations conditional on day of purchase for a set of days leading up to departure. Regardless of the timing of purchase, a significant proportion of cancellations occur within a day of booking. This time frame aligns with the Department of Transportation's twenty-four forgiveness period. Additionally, there is noticeable trend that indicates shocks arrive to consumers at decreasing rates as time passes after purchase. Overall, the figure demonstrates that a reasonable model of consumer choice must allow for heterogeneity in the probability that a consumer receives a shock and the rate of arrival of these shocks.

[7] See Appendix A.0.2 for further discussion.

Figure 1.7: Survival Function



Notes: The figure displays the Kaplan-Meier curve of cancellations conditioning on days after purchase. Each plot represents the survivor function of all purchases made on the specified day.

1.4 Model

In this section, I present the choice model of an airline consumer who is deciding when to purchase and which ticket to buy. The model characterizes a forward-looking consumer's purchase decision when valuation shocks can be realized after purchase. I assume that the consumer has rational expectations and views future prices as an exogenous stochastic process. The consumer's optimal purchase decision depends on their preferences and the uncertainty they face due to the arrival of negative idiosyncratic preference shocks similar to the optimal stopping problem of Rust (1987).

1.4.1 Outline and Utility

Let ℓ index a flight. Time is discrete $t = 0, 1, ..., T$, and the airline is able to sell tickets in each period. Flights depart at the end of period T. The timeline of events is as follows. Period t begins with realizations of preference shocks for all consumers holding tickets followed by their option to cancel. After the cancellation period, the airline sets the menu for the current period before any demand is realized. A subset of new consumers enters the market and learns the conditional value of their trip and their probability of travel. These new consumers and any consumer who previously entered the market but did not purchase observe the menu and form an expectation of all future menus. At this point, all consumers without tickets make their decision to purchase or delay until the next period.[8] Finally, the period ends, and the process repeats until the end of period T.

Consumer i seeks a ticket for a flight. Upon entering the market, the consumer searching for the ticket learns $\nu \subset \mathbb{R}$, the monetary base utility of travel. If the consumer purchases a class j ticket at time t, the conditional CARA utility of travel is given by

$$u_{jt}(p;\nu,\xi) = \frac{1-\exp\{-\alpha(\nu \times \xi_j - p_{jt})\}}{\alpha}, \tag{1.1}$$

where p_{jt} is the price of the ticket in class j in period t, $\xi_j \in [1,\infty)$ is the taste premium associated with flying in ticket class j, and $\alpha \geq 0$ is the Arrow-Pratt absolute risk aversion coefficient of the consumer. The outside option of not taking the trip is normalized to $u^* = 0$.

Because the airline assesses cancellation fees, the consumer must also consider the cost associated with canceling the trip. The consumer will only cancel if they receive a negative idiosyncratic shock that lowers the conditional utility of the trip to 0. At the time of purchase in period t, the cost of subsequently canceling in period τ is given by

$$f_{j\tau}(p,c) = \frac{1-\exp\{-\alpha(\max\{-p_{jt}, -c_{j\tau|t}\})\}}{\alpha}, \tag{1.2}$$

where $c_{j\tau|t}$ is the cancellation fee for ticket class j in period τ. The specification implies that the fee paid by the consumer is no more than the full cost of the ticket.

[8] In the model, there is no cost of delaying. The decision to purchase or delay will depend only on a consumer's preferences, the level of uncertainty that they face, and the expectation of future menus. Therefore, a consumer remains in the market until the flight departs but can choose not to purchase a ticket.

Thus, if consumer i is without a ticket in period $t \leq T$, their period t expected utility from purchasing a ticket in class j is given by

$$V_{jt} = \sum_{\tau=t+1}^{T} \left[\prod_{s=t}^{\tau-1} (1 - \rho_{s|t}) \rho_{\tau|t} f_{j\tau} \right] + \prod_{\tau=t+1}^{T} (1 - \rho_{\tau|t}) u_{jt} \tag{1.3}$$

where $\rho_{\tau|t}$ is the consumer's probability of receiving a preference shock in period τ given the period t purchase. Thus, the first term represents the expected cost of paying the cancellation fee, integrating over the probability of receiving the preference shock in each period following purchase, and the second term represents the expected utility of surviving until the departure date and taking the trip.

1.4.2 After Purchase

Motivated by the findings in Section 1.3.3, I model the arrival of utility shocks as a hazard function with baseline hazard rate given by

$$\rho_s = \lim_{ds \to 0} \frac{\Pr(x \in [s, s + ds) | x \geq s)}{ds}. \tag{1.4}$$

Here, x is the time elapsed between purchase and the arrival of the shock, and ρ_s represents the probability of surviving s periods before receiving the shock.

The shapes of the Kaplan-Meier curves in Figure 1.7 reveal that the probability of receiving a shock is decreasing as time passes after purchase. This is a property of the Weibull survival function with shape parameter less than one. Thus, I parameterize the hazard rate defined in Equation 1.4 as the Weibull hazard function with hazard rate

$$\rho_s = \lambda \gamma s^{\gamma - 1}, \; \gamma < 1.$$

Here, λ is the Weibull scale parameter, and γ is the Weibull shape parameter. These two parameters govern the intensity and persistence of the utility shocks, respectively. Utility shocks are drawn from this hazard function, and individuals have perfect information about the stochastic shock process. As is the case in Einav et al. (2010c), this assumption allows me to integrate over the continuous hazard rate to obtain the discrete time hazard rate that enters the consumer's choice model.

Given the assumed functional form of the hazard rate, let

$$S(\lambda, \gamma, s) = \exp\left(-\lambda s^{\gamma}\right) \tag{1.5}$$

be the Weibull survival function and let the discrete (daily) hazard rate $s = \tau - t$ periods after purchase be given by

$$\bar{\rho}_{\tau|t} = \frac{\int_t^{\tau-1} S(\lambda, \gamma, \tau - t)d\tau - \int_t^{\tau} S(\lambda, \gamma, \tau - t)d\tau}{\int_t^{\tau-1} S(\lambda, \gamma, \tau - t)d\tau}, \tag{1.6}$$

which is analogous to the product from Equation 1.3:

$$\bar{\rho}_{\tau|t} = \prod_{s=t}^{\tau-1}(1 - \rho_{s|t})\rho_{\tau|t}.$$

1.4.3 Before Purchase

The airline's problem is incredibly complex, as it dynamically optimizes ticket prices in each period in response to stochastic demand. The airline divides the plane into multiple cabins, including an Economy cabin with capacity K_E^{ℓ}. Within the Economy cabin, the airline offers ticket classes $j \in \{1, 2, 3\}$, creating a menu with the number of seats in ticket class j it is willing to sell, K_{jt}, and the price at which it is willing to sell them, p_{jt}, in each period t. From the consumer's perspective, prices evolve stochastically over time. For simplicity, I assume prices $\{p_t\}$ follow an exogenous first-order Markov process.

Because consumers have rational expectation of the price process, consumer i's optimal stopping problem at time t is represented as

$$\begin{aligned}\max_{\{d_\tau \in \{0,1,2,3\}\}_{\tau=t}^{T}} \mathbb{E}\Bigg\{ & \{d_t = j > 0\} V_{ijt} \\ & + \sum_{\tau=t+1}^{T-1} \left[\prod_{s=t}^{\tau-1} \{d_s = 0\}\{d_\tau = j > 0\} V_{ij\tau} \right] \\ & + \prod_{\tau=t}^{T-1} \{d_\tau = 0\}\{d_T = j > 0\} V_{ijT} + \{d_T = 0\} u^* \Bigg\} \end{aligned} \tag{1.7}$$

where the expectation is taken over the future prices conditional on the current price menu. Here, d_τ is the choice in period τ. $d = 0$ is the choice of not purchasing. The consumer will stop searching for a ticket at time τ when $d_\tau = j > 0$, where j is the choice of purchasing a class j ticket.

Because I have assumed rational expectations and full information about utility shocks, the consumer perfectly understands the process of future prices and the process of future preference shocks. In each period $t < T$, they observe the current set of prices $\{p_t\}$ and decide whether to purchase one of the available tickets. If the consumer purchases, they hold the ticket until they board the flight, receiving u_{jt}, or cancel if they receive a shock and pay $f_{j\tau}$. If the consumer chooses not to purchase in any period following their arrival, they receive the outside option u^*.

I normalize the E1 taste premium to one and specify ξ to be the taste premium for Economy 2 and Economy 3. Thus, the vector of parameters $h = (\nu, \xi, \alpha, \lambda, \gamma, \sigma)$ define the consumer, where σ is an additional parameter that represents the time at which the consumer begins to actively search for a ticket in the market.

1.5 Estimation and Identification

In this section, I discuss the estimation strategy and the sources of variation that allow for identification of the model parameters. The estimation of the parameters involves a method-of-moments approach similar to the two-step algorithms proposed in Fox et al. (2016), Nevo et al. (2016), and Aryal et al. (2021). First, I solve the dynamic program for a variety of candidate consumer types.

Second, I estimate a weight for each of the types by matching the weighted average of simulated optimal behavior, calculated in the first stage, to the analogous moments observed in the data. The result is an estimated distribution of types. In this section, I will outline the main steps.

1.5.1 Estimation

In the first step of the estimation, I construct a Markov price process unique to the two directional segments that connect each domestic airport pair in my sample. I then solve the dynamic program for each market-specific price process.

To begin, I discretize the class-specific price space of the price paths obtained from the kernel regressions used to construct Figure 1.2 for a given market κ. Additionally, I account for the event that a ticket is not available by creating a state with a price large enough ($\$100,000$) such that no consumer is able to purchase. I assign all prices along a price path for class j to a state n_j.[9] In order to capture the covariation between classes detailed in Figures 1.2 and 1.3, I then create a set of states for combinations of all three ticket classes, resulting in $N = n_1 \times n_2 \times n_3 = 1,620$ states in the market-specific transition matrix.

In addition to the interdependence of prices across classes, Figures 1.2 and 1.3 reveal that prices evolve at different rates over time. I allow for non-stationarity in the price process by finding the initial state probabilities 150 days before departure and calculating the conditional state transitions period-by-period until the day of departure using all of the price paths from the market.

I then solve the dynamic program for $10,000$ types at five different arrival times ($50,000$ total types). The initial $10,000$ types are drawn from a Halton quasirandom point set that fills the bounded multi-dimensional space uniformly. For market κ and consumer type $h = (\nu, \xi, \alpha, \lambda, \gamma, \sigma)$, I solve the finite-horizon dynamic program described in the previous section recursively, starting at the flight's departure date and working backwards to the candidate arrival date. The solution to the dynamic program for each type of consumer is characterized by the expected value functions and the policy functions that detail the consumer's choice for every price state in each time period.

[9] $n_1 = 9$, $n_2 = 12$, and $n_3 = 15$.

In the second step of the estimation, I choose a weight for each candidate type to match moments recovered from the data to the (weighted) average of the simulated outcomes from the model. Formally, the weights satisfy

$$\widehat{\beta} = arg \min_{\beta} \; m_\kappa(\beta)' \widehat{V}^{-1} m_\kappa(\beta) \tag{1.8}$$

$$\text{subject to} \quad \sum_{h=1}^{H} \beta_h = 1 \quad \text{and} \quad \beta_h \geq 0 \;\; \forall \beta.$$

The vector $m_\kappa(\beta)$ is given by $m_\kappa(\beta) = \widehat{m}_\kappa^{\text{dat}} - \widehat{m}_\kappa^{\text{sim}}\beta$, where $\widehat{m}_\kappa^{\text{dat}}$ is the vector of market-specific moments recovered from the data and $\widehat{m}_\kappa^{\text{sim}}\beta$ is the weighted average of the analogous type-specific moments predicted by the model simulation. $\widehat{V}^{-1}$ is a weighting matrix, specified as the identity matrix in the estimation routine.

The type weights, β_h, match the moments in each market, summing to 1 and bounded below by 0. In order to calculate standard errors, I sample the data of consumer transactions with replacement, employing the block-resampling methodology. For each sample, I recalculate the moments and then re-estimate the weights. Standard errors are calculated by repeating the process using the 1,000 different draws and estimates of the weights.

1.5.2 Identification

The data I use to identify the parameters include ticket choices, prices, and cancellations. As is detailed in Nevo et al. (2016), the objective function is linear in the weights, and identification is similar to that of a linear regression. The identification argument relies on variation both within and across flights in the market. I will discuss the moments I calculate and provide intuition for how these moments identify the parameters.

The moments calculated from cancellations provide identification of the distribution of uncertainty parameters. Because consumers have perfect information about the arrival of utility shocks, the timing of cancellations and the total proportion of consumers who cancel, both conditional on day of purchase, reveal the scale and shape of the survival functions. A high value of λ leads to a greater probability of cancellation in any period after purchase, especially the first period, while a high value of γ leads to a greater probability of holding the ticket for an extended period of time before cancellation.

Conditional on λ and γ, variation in prices, both within and across flights, identifies the distribution of the utility and taste premium parameters. The marginal densities of the prices for each ticket class and the marginal densities of the premiums in price between classes provide sufficient information to identify the distribution of ν and ξ. In particular, the price of an E1 ticket is informative of the base utility of travel while the prices of E2 and E3 tickets reveal the taste premium for higher quality.

Finally, ticket class shares, the distribution of purchase dates, and variation in prices across time within a flight identify the distribution of consumers' risk aversion and arrival date. Primarily, the day-to-day variation in prices maps to the consumers' cost of waiting. It is evident that consumers must arrive before purchasing, so an early purchase date is indicative of an early arrival date. When prices are expected to be stable for the near future, a consumer can wait to be more certain of travel without the risk of prices increasing. Additionally, the potential risk deters a consumer with high α from waiting. In general, consumers with high values of α will pay more for tickets with greater refunds and purchase soon after arrival.

1.6 Results and Counterfactuals

I estimate a weight greater than 0.1% ($\beta_h > 0.001$) for 235 types across the 8 markets. There is a great deal of variation across markets, with 14 to 43 types receiving positive weight depending on the market. However, in each market, there are 3 to 5 types that account for approximately half of the observed consumer behavior.

1.6.1 Results and Fit

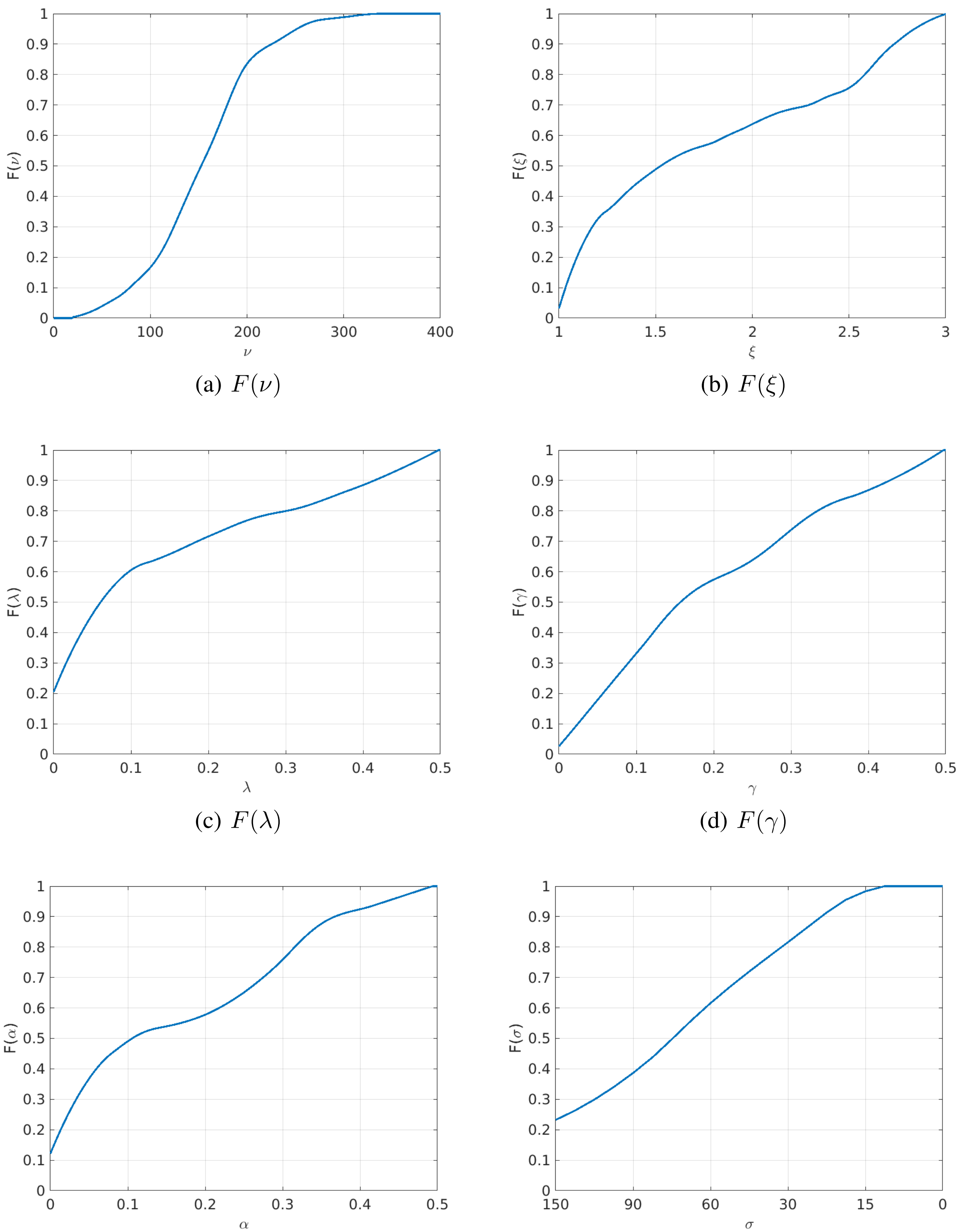
The estimated weights provide information about the heterogeneity across markets and consumers. To illustrate this heterogeneity, Figure 1.8 depicts the marginal cumulative densities of the six model parameters. The estimated distributions of the two preference parameters, (a) ν and (b) ξ, in particular seem reasonable. More than 80% of the consumers have an estimated base utility, ν, within $\$100$ of the average price of an Economy 1 ticket within their market, and approximately two-thirds of consumers have a premium, ξ, of less than twice their base utility for a higher class ticket.

The marginal densities of the uncertainty parameters, (c) λ and (d) γ, indicate that the majority of consumers have a relatively low level of uncertainty. Approximately half of the consumers are characterized by a λ less than 0.05, which roughly corresponds to 5% of receiving a shock within one day. The distribution of γ indicates that the persistence of shocks is relatively low, as well. In fact, consumers characterized by the median values of λ and γ have a survival rate of more than 91% thirty days after purchase.

Finally, the parameters α and σ provide information on the consumers' risk preferences and arrival date. The distribution of α indicates that airline consumers tend to be close to risk-neutral. This is perhaps unsurprising given the nature of air travel and the cost of airline tickets relative to average household incomes. Together, these variables also reveal how willing a consumer is to wait before purchasing after arrival. Consumers simulated from the model wait between two and three weeks on average, but a large mass purchase immediately after arrival.

The flexibility of the estimation procedure allows for the identification of the covariation between the parameters without any assumptions. This is especially useful due to the importance of the relationship between the parameters in the consumers' utility function and the effect they have on the decision-making process. Figure 1.9 shows a selection of the joint densities of the parameters. There is not a clear correlation between the preference parameters, ν and ξ, and the uncertainty scale parameter, λ. Previous studies of sequential screening in the airline industry often assume

Figure 1.8: Marginal Density of Parameters



(a) $F(\nu)$ (b) $F(\xi)$

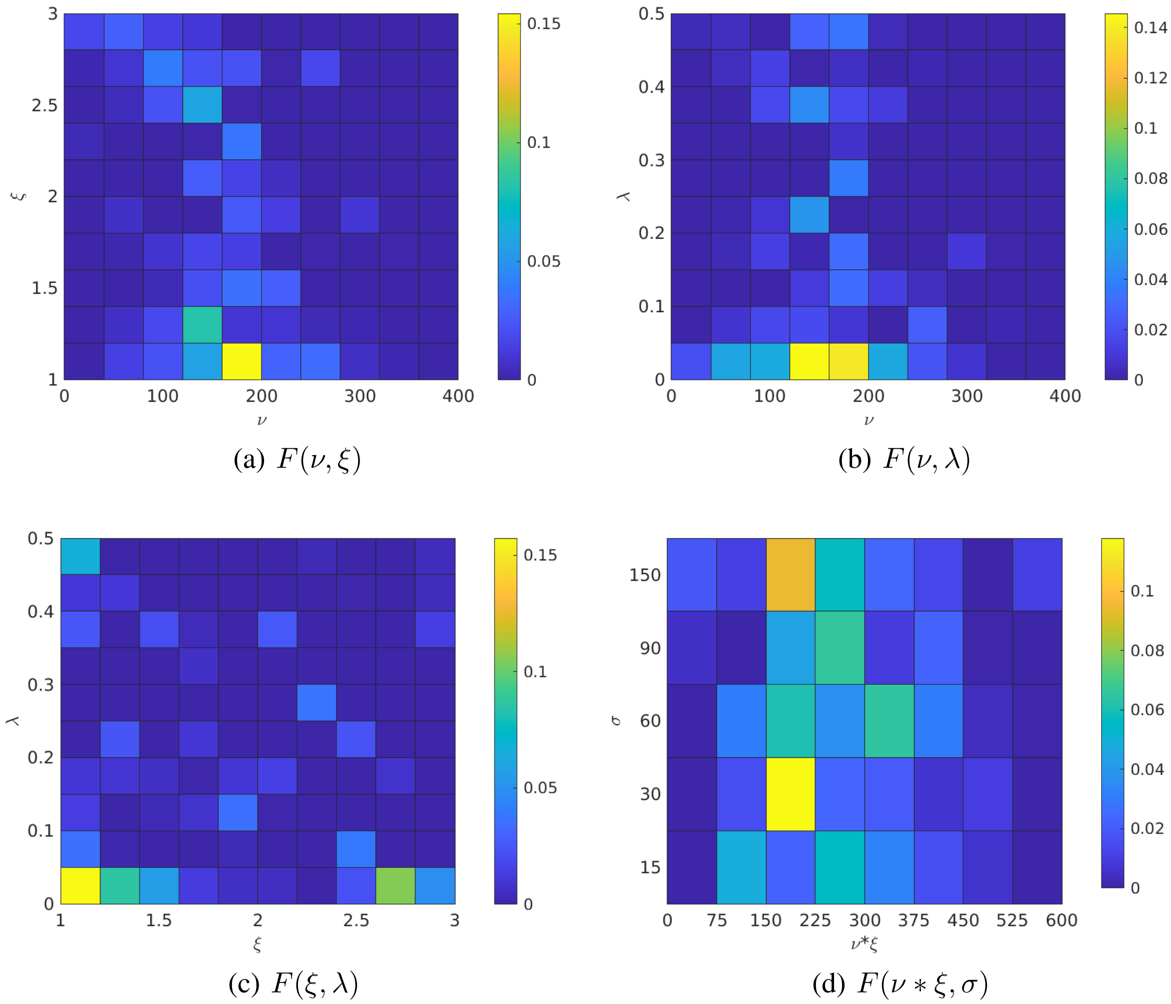
(c) $F(\lambda)$ (d) $F(\gamma)$

(e) $F(\alpha)$ (f) $F(\sigma)$

Note: The figures show the marginal cumulative densities of the model parameters.

that preferences and uncertainty are positively correlated.[10] Although this assumption is driven mostly by anecdotal evidence of the business traveler and leisure traveler, this finding indicates that relaxing this assumption allows for a more accurate representation of the consumer heterogeneity.

Figure 1.9: Joint Density of Parameters



(a) $F(\nu, \xi)$

(b) $F(\nu, \lambda)$

(c) $F(\xi, \lambda)$

(d) $F(\nu * \xi, \sigma)$

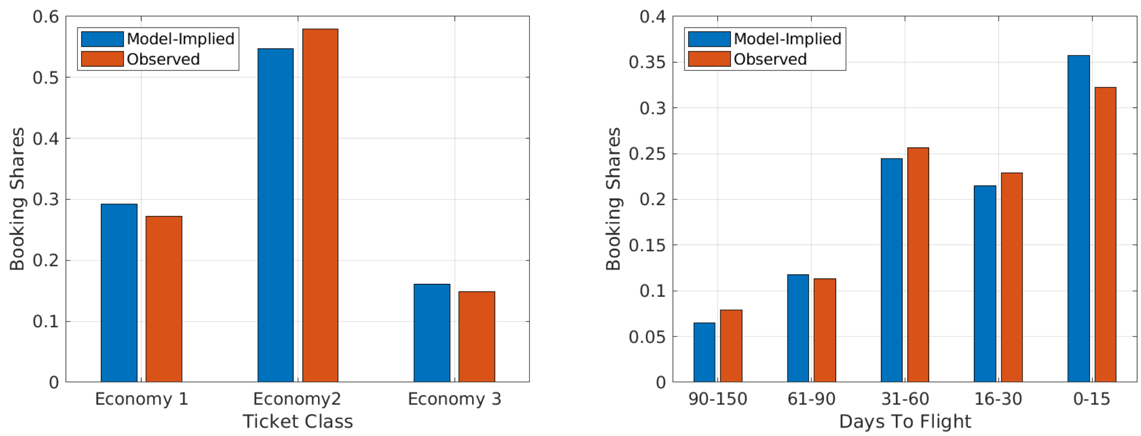
Note: The figures show a selection of the estimated joint densities of the model parameters.

Figure 1.10 assesses the model fit. I rely heavily on two sets of moments to identify the model parameters: the ticket classes shares and the timing of purchases. The observed and model-implied moments class shares and timing of purchase shares are extremely close. The model slightly overestimates the number of consumers who wait until the final day to purchase. This is likely due

[10]See Courty and Li (2000) and Escobari and Jindapon (2014).)

how the expected utility of the cancellation fee, and the fact that consumers who wait until the last period in the model never receive a shock after purchase. In reality, uncertainty is not fully resolved until the plane departs.

Figure 1.10: Model Fit



(a) Ticket Class Shares (b) Timing of Purchases

Note: The figures compare moments from the data to those implied by the estimated model. These moments include (a) ticket class shares and (b) timing of purchases.

1.6.2 Counterfactuals

Given the revenue management process, I run counterfactual analyses of alternative refund strategies in which I estimate profit, consumer surplus, and total surplus in the domestic markets using the structural estimates described in the previous section. In the first counterfactual, I remove the DoT twenty-four cancellation policy in an effort to explore its impact. Table 1.4 shows the percent change in a set of important measures after the policy is removed. Consumers are reluctant to buy tickets, and a greater share of those that do purchase tickets select the E3 ticket, which is the most expensive, because it is the only one that provides a full refund. Consumer surplus falls, but revenue increases. However, the revenue increase is not enough to offset the decrease in consumer surplus, so total surplus also falls.

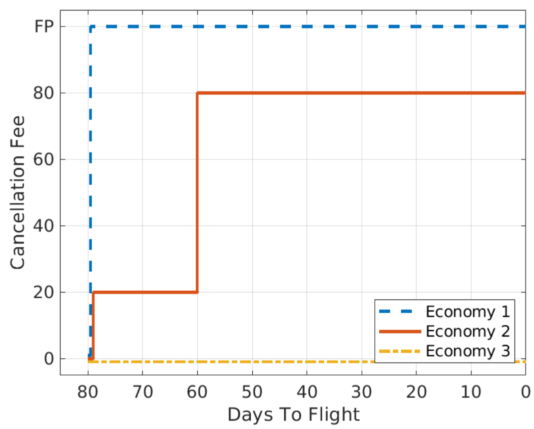
In the second counterfactual, I implement a cancellation fee schedule for Economy 2 tickets that is increasing steadily over time from the day of purchase. This schedule fits more closely to

Table 1.4: Counterfactual 1

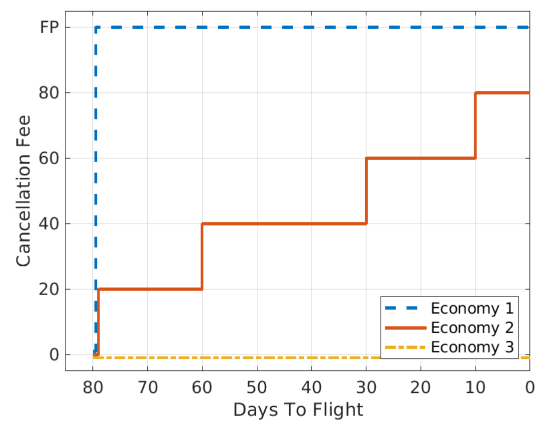
%Δ Passengers	%Δ E3 Bookings	%Δ CS	%Δ Revenue	%Δ TS
−0.13%	+5.16%	−0.53%	+0.38%	−0.17%

the pattern of observed cancellations and reduces the average cancellation fee paid by consumers. Figure 1.11 shows the difference between the airline's original cancellation fee schedule and the cancellation fee schedule implemented in the counterfactual.

Figure 1.11: Counterfactual 2



(a) Original Fee Schedule



(b) New Fee Schedule

Table 1.5 shows the impact of the proposed cancellation fee schedule. The number of passengers served is relatively unchanged, but the share of E3 bookings falls by a large margin due to consumers switching from E3 to E2. Overall, consumer surplus is increasing but not enough to offset the decrease in revenue, so total surplus also falls. Another result of this counterfactual refund policy is that the number of consumers who pay cancellation fees actually increases. However, the average cancellation fee is less, and consumer welfare as a whole is improving.

Table 1.5: Counterfactual 2

%Δ Passengers	%Δ E3 Bookings	%Δ CS	%Δ Revenue	%Δ TS
−0.02%	−14.22%	+0.10%	−0.36%	−0.08%

1.7 Conclusion

Uncertainty amongst consumers causes the initial allocation of goods to be suboptimal. Though there are a number of mechanisms that can alleviate these inefficiencies, the burden of reallocation falls solely on the seller if refunds are the only mechanism in the industry. In the airline industry, where valuation and uncertainty are assumed to be correlated, screening on uncertainty with a menu of options vertically differentiated in quality and refundability is widely practiced. I first showed that valuation and uncertainty are not necessarily correlated in the data provided to me by a North American airline, an important finding in the evaluation of refund policies in the industry. I then estimated a structural model without restricting the covariation of these demand aspects and used it to evaluate the impact of counterfactual refund policies.

The results suggest that the more lenient policy is worse for the airline and total welfare if prices and transitions are held fixed, but consumers are actually better off. With a more responsive price process, the losses to the airline and total welfare are reduced, and the change to consumer surplus remains positive. These findings indicate that screening on consumers on willingness to pay and uncertainty with the specified menu of ticket options may be suboptimal, or offer only modest improvements, if consumer preferences and uncertainty are not correlated as expected.

Finally, the analysis opens the door for several avenues of future research. The counterfactual exercises suggest that exploring how the correlation between preferences and uncertainty affect the optimality of various refund strategies could be beneficial for refund policy design across a number of industries. A next step would be to investigate the performance of the more lenient strategy in the real-world. There is precedent for such strategies, as Southwest Airlines does not charge any fees for canceling and Delta Airlines offers both a fully-refundable and non-refundable option for some ticket classes.

APPENDIX A: APPENDIX

A.0.1 Bookings

The choice of ticket is directly affected by the menu of available ticket classes. In Table A.1, I examine this effect for both segment types. When all tickets are available, the majority of consumers are choosing between the E1 and E2 tickets. This is especially evident by observing the proportions of the two remaining tickets when the E1 ticket is unavailable. The proportion of E3 consumers is nearly equivalent regardless of which lower class tickets are available.

Table A.1: Bookings and Availability

	Sample	Economy 1	Economy 2	Economy 3
Domestic				
Booking Shares				
All Available	87.37%	33.44%	54.05%	12.51%
E1 Unavailable	11.33%		86.63%	13.37%
International				
Booking Shares				
All Available	82.27%	32.06%	61.20%	6.74%
E1 Unavailable	15.13%		92.38%	7.62%

Note: The table provides additional descriptive statistics on itinerary bookings. The included statistics are the proportion of bookings on each segment type conditional on the tickets available.

The data provide additional insight into the itineraries of consumers. Some additional descriptives of the itineraries are presented in Table A.2. Consumers who book one way itineraries tend to purchase closer to departure on average. These consumers also book a higher proportion of E3 tickets and pay a higher fare on average. The differences across itineraries is much more extreme when comparing single passenger bookings with bookings of groups. Single consumers book more than two weeks later on average and are much more likely to purchase a higher ticket class. Overall, these finding indicate that consumers who are flying alone and booking only one flight at a time purchase closest to departure, but groups with round trip itineraries book far in advance, taking advantage of cheaper prices.

Table A.2: Booking Descriptives

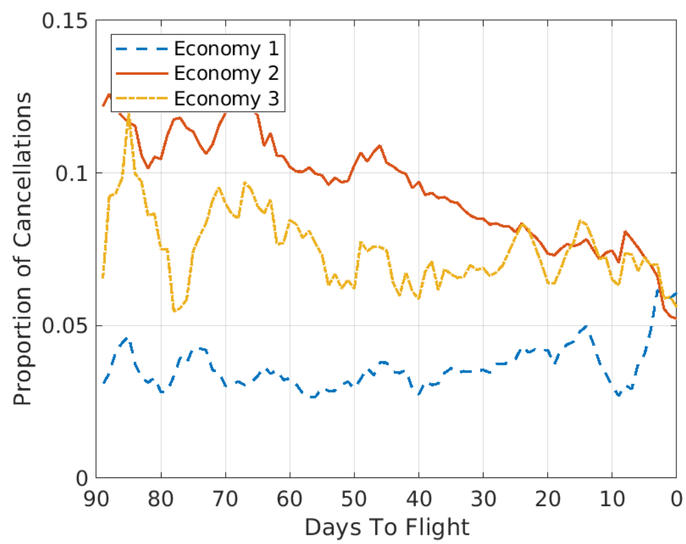
	Economy 1	Economy 2	Economy 3
One Way			
Booking Shares	29.04%	57.07%	13.89%
Transaction Price			
Mean	\$135.53	\$206.62	\$313.26
SD	\$52.39	\$95.19	\$144.33
Advance Purchase Days			
Mean	46.5	34.8	20.0
SD	31.5	34.2	26.6
Round Trip			
Booking Shares	27.35%	63.11%	9.54%
Transaction Price			
Mean	\$121.71	\$175.39	\$240.69
SD	\$41.86	\$64.91	\$89.18
Advance Purchase Days			
Mean	49.2	37.6	31.4
SD	30.1	31.8	28.5
1 **Passenger**			
Booking Shares	26.72%	60.20%	13.08%
Transaction Price			
Mean	\$129.57	\$195.85	\$288.82
SD	\$48.78	\$85.45	\$132.53
Advance Purchase Days			
Mean	43.7	30.6	20.2
SD	29.1	29.7	24.4
2+ **Passengers**			
Booking Shares	33.49%	57.71%	8.80%
Transaction Price			
Mean	\$110.17	\$140.51	\$221.67
SD	\$51.72	\$69.97	\$134.47
Advance Purchase Days			
Mean	57.5	54.6	40.8
SD	33.3	37.3	35.4

Note: The table provides descriptive statistics on itinerary bookings. The included statistics are the proportion of ticket class bookings for each itinerary type, the average and standard deviation of the transaction prices, and the average and standard deviation of the advance purchase days.

A.0.2 Cancellations

Because Economy 2 tickets are booked earlier on average than Economy 3 tickets, there are more days after purchase for a consumer to receive a utility shock that leads them to cancel. Figure A.1 shows the proportion of consumers who cancel by day of purchase and ticket class. The figure reveals two key findings. First, the plots are decreasing on average for E2 and E3 tickets, providing further evidence that consumers who book closest to departure are the least likely to cancel. Second, the plot of the E2 cancellations is greater than the E3 plot for the majority of the purchase days leading up to the final month before departure. This indicates that E2 tickets are more likely to be canceled by consumers who purchase well in advance of departure, which is more common in some international segments and, more generally, tourism segments.

Figure A.1: Cancellation Rate by Day of Purchase



(a)

Note: The figure displays the proportion of consumers who cancel their ticket by day of purchase and ticket class.

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