Analysis of U.S. Airline Passengers’ Refund and Exchange Behavior Across Multiple Airlines

Dan C. Iliescu
Laurie A. Garrow
Georgia Institute of Technology, Atlanta, GA

Roger A. Parker
Boeing Commercial Aircraft, Seattle, WA

1. Introduction and Motivation

Airlines use revenue management (RM) to decide how many seats (associated with a set of prices) should be made available for sale to customers. However, since all customers who request seats do not actually travel, airlines overbook to reduce the expected number of empty seats on flights when there is demand for those seats. Cancellation and no show rates are used to determine the overbooking level, i.e., the number of seats authorized for sale that exceed the capacity of the flight. The difference between cancellation and no show models relates to when the airline knows passengers do not intend to use their reservations. Cancellation models predict how many passengers inform the airline they do not intend to travel prior to the departure of their flights while no show models estimate the number of remaining booked passengers, i.e., passengers who have not cancelled, but fail to show for their flights.

Despite the fact that small improvements of 5-10% in the forecasting accuracy of these models can translate to millions of dollars in annual revenue for an airline (Neuling, et al. 2004), the cancellation models used in practice are fairly simplistic. Based on a review of the academic literature and practitioner conference proceedings, it was determined that most, if not all, cancellation models are based on historical averages that consider the influence of a small number of covariates associated with an itinerary (e.g., day of week, departure time, origin and destination, etc.) or with a booking (e.g., booking class and group size). Moreover, these models assume these covariates do not vary with time.

Different types of cancellation models are discussed in the literature, but generally fall into two categories. The first category of models predicts the probability of survival from one period to the next while the second category directly predicts the probability a booking survives until flight departure. For example, the cancellation model described by Westerhof (1997) in Figure 1 divides the booking horizon1 into T separate booking periods. By definition, a booking that exists at booking period t survives until booking period t+1 with probability \( p_t \) and is cancelled with probability \( \left(1 - p_t\right) \) for \( t > \) the departure day of the flight. The probability a booking that exists at time \( t \) survives until departure is given as \( p_t \times p_{t+1} \times \cdots \times p_{T-1} \times \left(1 - \text{no show rate}\right) \). Values for \( p_t \) are empirically derived from historical data. However, it is important to note that this model assumes cancellation probabilities are independent of when passengers book. Thus, conceptually, \( p_T \) does not depend on whether the bookings that exist at time \( T \) are from business

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1 The booking horizon is defined as the period during which an individual can make reservations for a flight. The typical booking horizon for an airline is 330 days.
passengers who booked in period $T-1$ or from leisure passengers who booked far in advance of the flight departure at time period $t$.

![Figure 1: Cancellation Model Described by Westerhof (1997)](image)

While Westerhof’s model predicts the probability a booking that exists at time $t$ will survive until the next period, Talluri and van Ryzin (2004) note that it is also common to directly model the number of bookings that survive until departure using a binomial distribution defined by $q_t$, the probability a booking at time $t$ survives until departure\(^2\). The authors reference a Tasman Empire Airways study (Thompson 1961) as empirical evidence on the validity of the binomial distribution assumptions (i.e., that (1) customers cancel independently of each other; (2) each customer has the same probability of cancelling; and, (3) cancellation probabilities are “memoryless” in the sense that they depend only on the time to flight departure and not on when the booking was first created). In contrast, Westerhof notes in his 1997 study of data from KLM that cancellation rates are not memoryless. However, while recognizing this phenomenon, Westerhof does not propose a methodology that can simultaneously incorporate these two dimensions of time.

This study addresses the limitation noted in the literature and uses survival analysis methods to simultaneously incorporate the time of booking and time to departure. A model of airline passengers’ “cancellation” behavior is estimated based on the occurrence of exchange and refund events in a sample of ticketing data from the Airline Reporting Corporation (ARC). Survival analysis methods are used to explore the pattern of cancellation probabilities over time and to determine the extent in which the observed heterogeneity of tickets (i.e., predictors) changes that pattern. With respect to the pattern of cancellation probabilities over time, survival models are used to predict the conditional probability that a purchased ticket will “be cancelled” in a time period given it survived up to that point (hazard probability). With respect to the observed heterogeneity, survival models are used to explore the amount of variation induced by different predictors in the hazard probability. Empirical results based on a Discrete Time Proportional Odds model indicate that cancellation rates are indeed influenced by both the time of booking and time until departure, in addition to a many other covariates (including departure day of week, market, group size, etc.).

\(^2\) Note that for time period $T$, $q_T$ is the no show probability. Talluri and van Ryzin (2004) also discuss possible refinements to the binomial model (inflation of variance of the show demand; moment generating functions) for datasets in which the percentage of groups is large.
This study contributes to the literature in two distinct ways. With respect to air travel behavior, this is the first study of airline passengers’ cancellation behavior based on survival methods. The study comprehensively examines the impact of time of purchase, time until departure, and directional itinerary and booking covariates. With respect to airline data, it is the first published study based on ticketing data from ARC. The use of this data was motivated by the business need of Boeing Commercial Aircraft to develop a cancellation model applicable to multiple carriers. However, the occurrence of cancellations in the ticketing data was much lower (1-8%) than rates reported in the literature for booking data (50% combined no-show and cancellation rates (Smith et al. 1992)). While this finding provides new insights into the underlying causes of cancellations, it also required the development of a modeling framework to link cancellation models based on booking data to cancellation models based on ticketing data. This conceptual framework represents the second main contribution of this work.

The remainder of this paper contains five sections. First, a description of the ARC ticketing data and variables available for analysis are described. Next, the conceptual framework for relating cancellation models derived from booking data and cancellation models derived from ticketing data is described. The third section describes the survival analysis methodology while the fourth section presents empirical results. Finally, on-going work and extensions to the analysis presented in this paper are described.

2. Data and Variables

It is important to emphasize from the outset that this study is based on ticketing data. This is in contrast to the booking data sources that are used by airlines to develop cancellation models. In order to assess the viability of using ticketing data from the Airline Reporting Corporation (ARC) for cancellation modeling, a sample of ticketing data was obtained. However, because ARC is owned by the airlines, extensive discussions were required to determine a data format that could support modeling objectives while protecting airline confidentiality. Specifically, individual tickets are used for the analysis, but each airline code has been replaced by a randomly assigned number and flight information (including flight numbers, departure and arrival times, number of stops, etc.) has been suppressed. The data used for this study contains simple one-way and round-trip tickets for which the outbound departure date occurred in 2004. As shown in Table 1, a total of eight directional markets are included in the analysis and reflect a mix of business and leisure markets and a mix of round trip and one ways. Each market is served by at least three airlines and contains non-stop and connecting itineraries. The markets include travel in origin destination pairs involving Miami, Seattle, or Boston (specifically, MIA-SEA, SEA-MIA, MIA-BOS, BOS-MIA, BOS-SEA, SEA-BOS) in addition to travel between Chicago O’Hare airport and Honolulu (ORD-HNL, HNL-ORD). Overall, 1.3% of the tickets are refunded and 1.2% are exchanged, but there are large differences across markets. While carrier confidentially considerations restrict the amount of flight-level information available for analysis, the sample data is unique in its ability to capture information about the time until exchange and refund events across multiple markets and multiple carriers.

3 A “simple” ORD-HNL one-way itinerary is one in which the trip starts in ORD and ends in HNL. The passenger is embarks at ORD (i.e., there are no flight segments before ORD) and disembarks at HNL (i.e., there are no flight segments after HNL). Similar logic applies to round-trip itineraries.
Table 1: Refund and Exchanges by Market and Trip Type

<table>
<thead>
<tr>
<th>Market</th>
<th># tickets</th>
<th># (%</th>
<th>Refunded</th>
<th>Exchanged</th>
<th>One Ways</th>
<th>Round Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>MIA-SEA</td>
<td>8,599</td>
<td>623</td>
<td>(7.2%)</td>
<td>84</td>
<td>(1.0%)</td>
<td>4,095</td>
</tr>
<tr>
<td>SEA-MIA</td>
<td>18,059</td>
<td>210</td>
<td>(1.2%)</td>
<td>198</td>
<td>(1.1%)</td>
<td>3,433</td>
</tr>
<tr>
<td>BOS-MIA</td>
<td>84,752</td>
<td>858</td>
<td>(1.0%)</td>
<td>1,248</td>
<td>(1.5%)</td>
<td>9,013</td>
</tr>
<tr>
<td>MIA-BOS</td>
<td>23,800</td>
<td>106</td>
<td>(0.4%)</td>
<td>318</td>
<td>(1.3%)</td>
<td>9,778</td>
</tr>
<tr>
<td>BOS-SEA</td>
<td>35,204</td>
<td>374</td>
<td>(1.1%)</td>
<td>423</td>
<td>(1.2%)</td>
<td>6,337</td>
</tr>
<tr>
<td>SEA-BOS</td>
<td>34,564</td>
<td>288</td>
<td>(0.8%)</td>
<td>442</td>
<td>(1.3%)</td>
<td>6,178</td>
</tr>
<tr>
<td>HNL-ORD</td>
<td>5,261</td>
<td>62</td>
<td>(1.2%)</td>
<td>51</td>
<td>(1.0%)</td>
<td>1,715</td>
</tr>
<tr>
<td>ORD-HNL</td>
<td>24,131</td>
<td>416</td>
<td>(1.7%)</td>
<td>138</td>
<td>(0.6%)</td>
<td>1,664</td>
</tr>
<tr>
<td>TOTAL</td>
<td>234,370</td>
<td>2,937</td>
<td>(1.3%)</td>
<td>2,902</td>
<td>(1.2%)</td>
<td>42,213</td>
</tr>
</tbody>
</table>

From a modeling perspective, it is generally believed that cancellation rates differ for business and leisure passengers. For example, business passengers who are more time-sensitive and require more travel flexibility may be more likely to modify their itineraries than leisure passengers, leading to higher cancellation and no show rates. While airlines do not explicitly collect information about trip purpose, trip purpose can be inferred from several other booking, non-directional itinerary, and directional itinerary variables. An itinerary is defined as a flight or sequence of flights that connects an origin and destination. Non-directional itinerary information does not distinguish whether passengers on a flight from MIA-SEA are traveling outbound from MIA to SEA (as reflected in the MIA-SEA row in Table 1) or inbound from SEA to MIA (as reflected in the SEA-MIA row in Table 1). While non-directional information is predominately used in airline’s RM systems, directional itinerary information provides a much richer set of variables from which trip purpose can be inferred. For example, business passengers are more likely to depart early in the week, stay a few nights, and return home later in the week (and thus not stay over a Saturday night). In contrast, leisure passengers are more likely to depart later in the week, stay more nights than a business passenger.

With respect to ARC data, ticketing information includes the issue date (or date the ticket was purchased), the outbound and inbound departure dates, outbound and inbound ticketing class (i.e., first letter of the fare basis code), ticketing cabin code (i.e., first, business, coach, other/unknown), net fare (i.e., fare that does not include taxes and fees), and total tax and fees. From the outbound and inbound departure dates, several variables commonly used to segment customers into business and leisure segments can be derived including departure and return days of week, length of stay, and trips that include a Saturday night stay. Tables 2 to 7 show the influence of these variables on exchange and refund rates. As shown in Table 2, the percentage of refunds and exchanges across different advance purchase values fluctuates. For tickets purchased 8 to 360 days from the outbound departure date, exchanges exhibit a “tub” shape, characterized by a higher propensity of tickets purchase well in advance from departure or in the 2 to 3 weeks from departure to be exchanged. Also, is worth noticing that exchanges drop dramatically one week from departure. In contrast, refunds tend to increase as the advance purchase decreases, that is, tickets purchased closer to the outbound departure date are more likely to be refunded. However, at 31-40 days from departure, there is a slight increase in the percentage of refunds which may be attributed to consolidator bookings (such as air travel associated with cruise lines that are present in the Miami and Seattle markets). Also, similar to
exchanges, the percent of refunds drops very close to departure, or 0-3 days from the outbound departure date.

Table 2: Refund and Exchanges by Advance Purchase

<table>
<thead>
<tr>
<th>Advance Purchase</th>
<th>Exchanges</th>
<th>Refunds</th>
<th>Exchange &amp; Refunds</th>
<th>Total Tickets</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-3</td>
<td>33</td>
<td>267</td>
<td>300</td>
<td>21825</td>
</tr>
<tr>
<td>4-7</td>
<td>245</td>
<td>483</td>
<td>728</td>
<td>21205</td>
</tr>
<tr>
<td>8-14</td>
<td>478</td>
<td>430</td>
<td>908</td>
<td>27607</td>
</tr>
<tr>
<td>15-21</td>
<td>426</td>
<td>312</td>
<td>738</td>
<td>26738</td>
</tr>
<tr>
<td>22-30</td>
<td>410</td>
<td>370</td>
<td>780</td>
<td>30988</td>
</tr>
<tr>
<td>31-40</td>
<td>333</td>
<td>445</td>
<td>778</td>
<td>28344</td>
</tr>
<tr>
<td>41-50</td>
<td>236</td>
<td>259</td>
<td>495</td>
<td>21904</td>
</tr>
<tr>
<td>51-90</td>
<td>421</td>
<td>197</td>
<td>618</td>
<td>30126</td>
</tr>
<tr>
<td>91-180</td>
<td>259</td>
<td>445</td>
<td>777</td>
<td>16618</td>
</tr>
<tr>
<td>181+</td>
<td>61</td>
<td>56</td>
<td>117</td>
<td>3176</td>
</tr>
</tbody>
</table>

Tables 3 and 4 show how a Saturday night stay and the number of nights away from home impact exchange and refund rates. Round trip tickets without a Saturday stay (that tend to be associated with leisure travel) are less likely to be exchanged or refunded. Similarly, as the number of nights spent away from home increases (which would indicate the trip is more likely to be leisure), the exchange and refund rates for round trip tickets decrease.

Table 3: Refund and Exchanges by Saturday Night Stays (Round Trip Tickets)

<table>
<thead>
<tr>
<th>Saturday Stay</th>
<th>Exchanges</th>
<th>Refunds</th>
<th>Exchange &amp; Refunds</th>
<th>Total RT Tickets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Saturday Stay</td>
<td>1,401</td>
<td>1,263</td>
<td>2,664</td>
<td>2,076%</td>
</tr>
<tr>
<td>No Saturday Stay</td>
<td>1,476</td>
<td>1,147</td>
<td>2,623</td>
<td>4,110%</td>
</tr>
</tbody>
</table>

Table 4: Refund and Exchanges by Number of nights away from home (Round Trip Tickets)

<table>
<thead>
<tr>
<th>Nights Away</th>
<th>Exchanges</th>
<th>Refunds</th>
<th>Exchange &amp; Refunds</th>
<th>Total RT Tickets</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1</td>
<td>304</td>
<td>271</td>
<td>575</td>
<td>6.204%</td>
</tr>
<tr>
<td>2</td>
<td>487</td>
<td>344</td>
<td>831</td>
<td>4.582%</td>
</tr>
<tr>
<td>3</td>
<td>538</td>
<td>295</td>
<td>833</td>
<td>2.986%</td>
</tr>
<tr>
<td>4</td>
<td>439</td>
<td>240</td>
<td>679</td>
<td>2.588%</td>
</tr>
<tr>
<td>5</td>
<td>213</td>
<td>168</td>
<td>381</td>
<td>2.156%</td>
</tr>
<tr>
<td>6</td>
<td>134</td>
<td>61</td>
<td>195</td>
<td>1.686%</td>
</tr>
<tr>
<td>7+</td>
<td>597</td>
<td>854</td>
<td>1,451</td>
<td>2.193%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>2,713</td>
<td>2,233</td>
<td>1,763</td>
<td>3,684%</td>
</tr>
</tbody>
</table>

The differences in exchange and refund rates between business and leisure travelers are also seen in Tables 5 and 6 that show the effect of outbound and inbound departure dates on refund and exchange rates. Exchanges are more likely to occur on Sunday, Monday, and Tuesday outbound departures and Wednesday, Thursday, and Friday inbound returns. Refunds exhibit a similar pattern, but also show a relative high rate on Saturday outbound departures.
Finally, Table 7 shows the exchange and refund rates by month of the outbound departure date and refunds and exchanges. No clear pattern can be detected, suggesting the effects of seasonality may be limited.

<table>
<thead>
<tr>
<th>Departure Month</th>
<th>Exchanges</th>
<th>Refunds</th>
<th>Exchange &amp; Refunds</th>
<th>Total RT Tickets</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>245</td>
<td>266</td>
<td>511</td>
<td>17,357</td>
</tr>
<tr>
<td>February</td>
<td>233</td>
<td>306</td>
<td>539</td>
<td>22,384</td>
</tr>
<tr>
<td>March</td>
<td>237</td>
<td>277</td>
<td>514</td>
<td>24,108</td>
</tr>
<tr>
<td>April</td>
<td>226</td>
<td>264</td>
<td>490</td>
<td>23,402</td>
</tr>
<tr>
<td>May</td>
<td>244</td>
<td>199</td>
<td>443</td>
<td>19,332</td>
</tr>
<tr>
<td>June</td>
<td>251</td>
<td>239</td>
<td>490</td>
<td>18,846</td>
</tr>
<tr>
<td>July</td>
<td>204</td>
<td>244</td>
<td>448</td>
<td>17,961</td>
</tr>
<tr>
<td>August</td>
<td>186</td>
<td>202</td>
<td>388</td>
<td>18,071</td>
</tr>
<tr>
<td>September</td>
<td>273</td>
<td>325</td>
<td>598</td>
<td>16,124</td>
</tr>
<tr>
<td>October</td>
<td>279</td>
<td>224</td>
<td>503</td>
<td>18,209</td>
</tr>
<tr>
<td>November</td>
<td>293</td>
<td>167</td>
<td>460</td>
<td>18,267</td>
</tr>
<tr>
<td>December</td>
<td>231</td>
<td>224</td>
<td>455</td>
<td>20,209</td>
</tr>
</tbody>
</table>

In addition to the variables described above, tickets that are refunded or exchanged also contain the date the refund or exchange was processed. In addition, when one ticket is exchanged for another ticket, information on the exchange fee and fare difference from the original ticket is available. Indicator variables are also populated to show the reason for the exchanged ticket. Specifically, indicators are used to know whether the customer requested (1) a new outbound and/or inbound departure date, (2) a new outbound and/or inbound ticketing class and cabin code, and/or (3) a new outbound and/or inbound itinerary.
The ticketing data used for this study is distinct from the data collected as part of the United States Department of Transportation (US DOT) Origin and Destination Data Bank 1A or Data Bank 1B (commonly referred to as DB1A or DB1B). The data are based on a 10 percent sample of flown tickets collected from passengers as they board aircraft operated by U.S. airlines. The data provide demand information on the number of passengers transported between origin-destination pairs, itinerary information (marketing carrier, operating carrier, class of service, etc.), and price information (quarterly fare charged by each airline for an origin-destination pair that is averaged across all classes of service). While the raw DB datasets are commonly used in academic publications (after going through some cleaning to remove frequent flyer fares, travel by airline employees and crew, etc.), airlines generally purchase Superset data from Data Base Products. Superset is a cleaned version of the DB data that is cross-validated against other data-sources to provide a more accurate estimate of the market size. See the Bureau of Transportation Statistics website at www.bts.gov or the Data Base Products, Inc. website at www.airlinedata.com for additional information.

Data based on the DB tickets differs from the ticketing data obtained from ARC for this study in three important ways. First, DB data reports aggregate information using quarterly averages and passenger counts while ARC data contains information about individual tickets. Second, DB data contains a sample of tickets that were used to board aircraft, or for which airline passengers “show” for their flights. In contrast, ARC data provides information about the ticketing process from the financial perspective. Thus, historical information is available for events that trigger a cash transaction (purchase, exchange, refund), but no information is available for whether and how the individual passenger used the ticket to board an aircraft; this information can only be obtained via linking with the ARC data with airlines’ day of departure check-in systems. Finally, ARC ticketing information does not include changes that passengers make on the day of departure; thus, the refund and exchange rates will tend to be lower than other rates reported by airlines or in the literature.

Given an understanding of the ticketing data used for this study, the next section describes the key business objectives, as these have a direct impact on the research design.

3. The Business Context and Relationship Between Booking & Ticketing Cancellation Models

From a business perspective, this research needs to integrate into the larger effort of Boeing Commercial Airplanes (BCA), the commercial products arm of The Boeing Company. Specifically, BCA has been engaged in a research effort to advance its models of passenger behavior. These models are a central part of the tools used by its marketing department to help potential airline customers estimate how much market share and revenue can be gained via the introduction of new service and equipment in a market. One of the core components of the passenger behavior models under development is the Universal Market Simulator (UMS) shown in Figure 1. The UMS is a Monte Carlo micro-simulation of airline revenue generation whose primary output is the revenue to an airline that results from the individual choices of thousands

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4 “The raw materials for the Origin-Destination survey are provided by all U.S. certificated route air carriers, except for a) helicopter carriers, b) intra-Alaska carriers, and c) domestic carriers who have been granted waivers because they operate only small aircraft with 60 or fewer seats.” (Data Base Products, 2006).

5 The website describes the data and federally-mandated reporting requirement for U.S. airlines.
of passengers moving over a world-wide airline network. The UMS uses several models to represent different aspects of passenger behavior and airline competitive responses including models for synthetic population generation, induced demand, booking and ticketing curves, ticket cancellations, passenger itinerary choice, and airline revenue management models (Parker et al., 2004).

The UMS is designed to simulate passenger behavior and airline competitive responses on a global network. Unlike individual airlines, however, BCA does not have access to the same data (such as an airline’s bookings and check-in information). Further, the quality and ability to obtain data varies throughout the world. Thus, in practice, when BCA works directly with an airline to help assess the revenue and market share impacts of introducing new equipment in a market, it is common to validate and adjust Boeing’s forecasting input to more accurately reflect the individual airline’s revenue management system, business process, and expectations of future market conditions. (For a flavor of the variability in airline policies related to ticketing, exchange and standbys, see the memo distributed by American Express, 2005). Consequently, given that booking (and not ticketing) data is the core of airlines’ revenue management systems, it is essential that the refund and exchange models developed in this study can be integrated into the UMS (specifically linked to cancellation and day-of-departure no-show and standby models) and be adjusted based on an individual airline’s business practice.

Figure 1: Boeing’s Universal Market Simulator (Parker, et al. 2004)

Figure 2 shows the relationships among bookings, tickets, cancellations, no-shows, and standbys from the perspective of a typical airline’s revenue management process. Revenue management is used to decide how many seats to allocate for sale to customers (prices for these seats are generally set outside the allocation decision and based on competitive market conditions). Booking data form the basis for these allocation decisions. Specifically, an airline decides the
number of seats to sell based on forecasts of how many current bookings will show for flights and how many future bookings will show for flights. Cancellation, no-show, and standby models are used to predict the number of bookings that will show for flights. These forecasts differ depending on when the airline knows the passenger does not intend to travel on the ticketed flight. As described in Garrow and Koppelman (2004a), cancellation models predict how many passengers inform the airline they do not intend to travel prior to the departure of their flights. Some airlines further distinguish between bookings that are made and cancelled within a short time period (like 24 hours) and bookings that are cancelled outside this time period. If a booking is made and cancelled within a 24 hour period (which generally corresponds to the amount of time after a booking is made that it must be ticketed), it is generally removed from the demand forecast as part of a “booking churn” model so it does not influence cancellation rates. There are several reasons for booking churn that include travel agencies making duplicate bookings or making bookings to hold inventory; for example, American Airlines defines churn as “any cancel/rebook activity intended to circumvent ticketing time limits or hoard inventory” (American Airlines, 2005).

In contrast to cancellation models, no-show models estimate the number of remaining booked passengers, i.e., passengers who have not cancelled, but fail to show for their flights. Standby models are used to predict the number of passengers who arrive to the airport but take a flight on the ticketing carrier that is different than the one they purchased. The benefit of identifying standbys lies in the recognition that as flights become full, opportunities to standby on different flight decrease and passengers are not able to standby for alternate flights but rather “show” for the flight they purchased (Garrow and Koppelman 2004a, 2004b).

Given the business objectives supporting this analysis, it is important to understand how ticket information from ARC relates to the show, no-show, cancellation, and standby models used by airlines that are based on booking data. From an airline perspective, show, no-show, standby, and cancellation rates are influenced both from bookings that are ticketed (i.e., paid for) as well as bookings that are not ticketed (i.e., reservation made but never paid for). As shown in Figure 2, bookings that are not ticketed ultimately become a churn booking, a cancellation, or a no-show. In contrast, bookings that are ticketed can end up in one of four states, namely a cancellation, a no-show, a standby, or a show. These states can be related to the ARC and DB ticketing data by noting the different ways these states can occur. For example, a cancellation that triggers a financial transaction occurs when a passenger informs the airline prior to departure that she does not intend to take the ticketed flight. In this case, the original booking that was purchased is cancelled from the revenue management system and a new booking (and ticket transaction) is created for the new flight(s) she purchases. These transactions appear in ARC data. However, there are also ticketed bookings that are cancelled that will not appear in ARC data. For example, some airlines use automated data processes that cancel the inbound flights of an itinerary if the passenger no-shows on the outbound flights. In this case, the outbound flights that were never used or exchanged prior to departure become no-shows and the carrier automatically cancels in the inbound flights (without generating an automatic refund / exchange transaction). However, from the perspective of assessing the revenue generation to an airline, these cancellations are not relevant to the business question at hand as the airline still receives the revenue from the original ticket transaction.
Similar to cancellations, there are two ways a ticketed booking can become a no-show and only one of these cases will appear in the ARC data. No-shows that occur due to exchanges or refunds requested after the flight departure are captured in ARC ticketing data; however, no-shows that occur when an individual purchases a ticket yet never uses it or requests a refund are not captured in the ARC data. As before, these no-shows are not relevant as the airline receives the revenue from the original ticket transaction.

In contrast to no-shows and cancellations, a show occurs when a ticket was used exactly as purchased. This “snapshot” of tickets is what is captured in the lifted tickets collected in the DB data collected by the U.S. DOT. Finally, it is important to note that changes to tickets that occur on day of departure for the flight are not captured in the ARC data, but rather are part of an individual airline’s check-in processing.

To summarize, unlike DB ticketing data or booking data from a single airline, ARC ticketing data provides an opportunity to develop no-show and cancellation models for multiple airlines and/or markets. Most important, the no-show and cancellation rates derived from ARC ticketing data directly tie to the revenue generation stream of an airline, which is one of the most important metrics to an airline considering aircraft purchases. At the beginning of the project, it was anticipated that the no-show and cancellation rates in ARC ticketing data would be representative of the typical rates seen in airline booking data (that is, the authors made the implicit assumption that the majority of booking transactions in an airline’s revenue management system were purchased before flight departure). Surprisingly, this was not the case. Refund and exchange rates in ARC ticket data were much lower (2-8%) than the 50% combined cancellation and no show rate that is generally quoted based on data from American Airlines (Smith, et al. 1992). Consequently, discussions are underway with ARC to obtain voided ticket information to capture booking churn, i.e., voided tickets are transactions that are “created” but “voided” or “cancelled” within a short period of time (usually two business working days) prior to the time payment is required. It is hoped that by extending the analysis to include voided tickets, we will gain a better understanding the underlying causes associated with booking churn that are driving the differences in these rates, which will allow the rates to be readily adjusted when working directly with a carrier’s data.
4. Methodology

Given the understanding of how ticketing refunds and exchanges relate to airline no-shows and cancellations, this section describes the study methodology. A discrete-time proportional odds (DTPO) survival model is used to predict the probability of a ticket being “cancelled” (i.e., refunded or exchanged before outbound departure date) at each day from departure. The DTPO approach differs from cancellation forecasting methods commonly used in the airline industry (e.g., Chatterjee 2001; Polt 1998; Ratliff 1998) and is similar in spirit with the cancellation model proposed by Westerhof (1997) shown in Figure 1. However, the DTPO approach is more flexible in that it extends the Westerhof’s formulation by examining the joint effects of multiple covariates affecting refund and exchange events of ticketed population and allowing time-varying covariates or variable effects of covariates over time.
4.1 General Taxonomy of Survival Analysis Models

Historically, statistical methods for time-to-event data were developed in the medical field and applied to epidemiological applications (that capture the time-to-occurrence of an event given exposure to an infection) or clinical applications (that capture the time-to-occurrence of an event given exposure to treatment). The fundamental difference between the two categories of studies consists in the way survival time is considered – either in retrospective or prospective (Kim & Lagakos, 1990). In retrospective studies, investigators analyze the disease incidence for exposed individuals “in hindsight” based only the prevalence of disease at the time the data is collected (Becker, 1989; Shiboski & Jewell, 1992). In contrast, in prospective studies investigators use a “forward looking” approach to analyze the evolution of disease for individuals exposed to various treatments (Hosmer & Lemeshow, 1999). Although survival analysis methods arise naturally for the medical field, they have been used in a wide range of contexts spanning demography, econometrics, transportation, etc. For a comprehensive review of survival analysis applications and how they fit in the general family of generalized additive models (GAM), see Shiboski (1998).

Since survival “methods are so similar in their underlying philosophy that they usually give similar results” (Allison, 1995), the choice of “the right” survival model depends on several substantive assumptions regarding the population at risk, the beginning and end of an observation, the censoring mechanism, whether the population is homogenous with respect to survival experience and the shape of the survival time distribution. The population at risk is defined as independent “subjects” under observation during parts or the entire period of the survival study. The beginning of an observation is uniquely identified by the time at which the subject becomes at risk of failure during the period of study. In contrast, the end of an observation can be identified either by the time at which the failure of the subject is observed (non-censored) or by the time at which the subject observation ends due to maximum observation time or to the subject being lost in the follow-up process (censored).

Furthermore, the main focus of the survival analysis changes depending on assumptions about population homogeneity with respect to the survival experience. Conceptually, if the assumption of population homogeneity holds, then the lifetimes of all subjects are governed by the same survival function \( S(t) \). In this case, the main focus of survival analysis is on determining the appropriate shape of the survival and hazard functions. However, if the assumption of population homogeneity does not hold, the focus of the analysis is expanded to include an exploration of the influence of a vector of covariates on survival time. In this exploration, the specific assumptions about the way in which the vector of covariates influences survival process define two main categories of models – proportional hazard models (PH) and accelerated failure time models (AFT). The fundamental difference between the two is that while AFT models coefficients represent changes in survival time due to a unit change in a given covariate, PH models coefficients represents changes in the hazard rates due to a unit change in a given covariate.

Finally, it is important to note that the time-to-event process can be interpreted using the results of either survival or hazard functions. The hazard function (the instantaneous risk that an event
will occur at time $t = h(t)$ is closely related\(^6\) to the survivor function (probability of survival beyond $t = S(t)$) and time-to-event density function ($f(t)$). As such, assumptions about the time-to-event density function are closely related to assumptions about the hazard function (e.g., the exponential density function will generate a constant hazard rate, the Gompertz density function a linear increase in hazard rate a.s.o.). Furthermore, the functional form of the hazard function is closely related to whether the time-to-event process is assumed to evolve along a continuous or discrete time scale. As a general rule, it is appropriate to use a continuous time scale when the ratio between the length of an observation (defined as the difference between the beginning and end of the observation) and the length of the time interval used for grouping the observations is high. Still, even when observations are generated on a continuous time scale but we have variable values of covariates over time or variable effects of covariates over time, the discrete-time survival models prove to be a good alternative. The next section presents the application of such a case for the ARC dataset, for which a Discrete-Time Proportional Odds (DTPO) was designed and tested.

### 4.2 Discrete Time Proportional Odds (DTPO) Model for ARC Data

The current DTPO model differs from the previous research on distribution of cancellation rates/proportions\(^7\) in four aspects. First, it relaxes the general assumption of population homogeneity and tests the influence of observed heterogeneity on cancellation rates/proportions considering different segmentations/covariates (length of stay, outbound departure day of week, departure month, market, carrier, group size, fare). Second, it assumes that heterogeneity across tickets is accounted for in these covariates and its effect is distinct from that of time (changes in covariates values produce only vertical shifts and no distortions in a “baseline” cancellation rate line). Third, by construction, the DPTO model accommodates time-varying effects of covariates, thus allowing for interactions between time of booking and days from departure to be explored. Finally, since the time-scale is discrete, the DTPO model has sufficient flexibility to test different distributional shapes for the baseline cancellation rate.

In order to define the scope of the current work, it is important to note that when compared to other applications of survival analysis, ARC ticketing data has several specific characteristics. The first characteristic is that tickets lifetimes are not followed using the classical Type I or Type II censoring process but rather limited by a random censoring process. Indeed, all tickets end either in failure (exchange/refund) or in a certain non-event which is outside of the control of the investigator (outbound departure date). Since in the case of an informative censoring process, this particularity of the data can generate problems, the Time of Booking should always be included in the model as a mean to control the estimation bias (Allison, 1995). The second characteristic is that out of the total population of exchange and refund events, a significant part (i.e., 25%) occurs after the outbound departure date. Since, as presented in Figure 2, there is a high chance that this percentage consists of no-shows, the current analysis makes use of those exchange or refund events that occur prior to the outbound departure. Furthermore it assimilates

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\(^6\) The formula that expresses the hazard function in terms of the p.d.f. and survivor function is:

$$h(t) = \frac{f(t)}{S(t)}$$

\(^7\) Chatterjee (2001) defines a **cancellation rate** at time $t$ as the proportion of those booked at $t$ which cancel by $t+1$ and a **cancellation proportion** at time $t$ as the proportion of those booked at $t$ which cancel by departure day.
these events with cancellations and thus develops a cancellation model for the outbound legs of an airline itinerary. The third characteristic is that the assumption of independence between observations is undoubtedly violated by the presence of groups. Therefore, the ARC dataset was transformed from an individual ticket level database to a group level database. More specific, observations determined to have the same values on the entire set of covariates with the same scrambled PNR value\(^8\) were eliminated and a variable indicating the group size added to the set of covariates. Taking into account all of the above characteristics, the ARC application will be defined as a **ticketing cancellation model on the outbound legs of an airline itinerary for groups**. Also, after data transformation has been applied, the original ARC dataset of 234,370 tickets (1.3% -Refunds; 1.2%-Exchanges) has been transformed to 164,288 distinctive groups (2.2% -Cancellations).

### 4.3 Model Formulation and Estimation

Using the transformed ARC Data as backbone, the Discrete Time Proportional Odds (DTPO) model partitions the time-to-event time-scale \([0, t_1]\) of the \(i^{th}\) ticket into a number of \(k\) disjoint time intervals \([t_0, t_1), (t_1, t_2), (t_2, t_3), \ldots, (t_{k-1}, t_k]\). The time origin \(t_0\) of a ticket (observation) is the Issue Date or the Time of Booking. The disjoint interval bounds \(t_1, t_2, \ldots, t_{k-1}\) are days from departure (DFD) starting with the time of booking until either the time of departure or time of cancellation of ticket \((t_k)\). Furthermore, the discrete hazard for a ticket \(i\) in the \(k^{th}\) interval is defined as the conditional probability that ticket \(i\) will experience the cancellation event in the \(k^{th}\) interval given survival up to that point (Equation 4.1). Using conditional probability theory, it follows that the probability that an “uncensored” ticket will experience the cancellation in the \(k^{th}\) interval is equal with the product between the conditional probabilities that the cancellation did not occur in intervals 1 to \(k-1\) and did occur in interval \(k\) (Equation 4.2). Similarly, the probability that a “censored” ticket will experience the cancellation after the \(k^{th}\) interval is equal with the product between the conditional probabilities that the cancellation did not occur in any of the \(k\) intervals (Equation 4.3).

\[
\begin{align*}
\hat{h}_k &= P(T_i = k \mid T_i \geq k) \\
\end{align*}
\]

\[
\begin{align*}
P(T_i = k) &= P(T_i = k \mid T_i \geq k) \cdot P(T_i \neq k-1 \mid T_i \geq k-1) \ldots P(T_i \neq 1 \mid T_i \geq 1) \\
P(T_i = k) &= h_k \cdot (1 - h_{i(k-1)}) \cdot (1 - h_{i(k-2)}) \ldots (1 - h_{i1}) \\
\end{align*}
\]

\[
\begin{align*}
P(T_i > k) &= P(T_i \neq k \mid T_i \geq k) \cdot P(T_i \neq k-1 \mid T_i \geq k-1) \ldots P(T_i \neq 1 \mid T_i \geq 1) \\
P(T_i > k) &= (1 - h_k) \cdot (1 - h_{i(k-1)}) \cdot (1 - h_{i(k-2)}) \ldots (1 - h_{i1}) \\
\end{align*}
\]

As a result, the likelihood contribution for uncensored and censored tickets can be expressed using Equations 4.4 and 4.5, which permits to express the likelihood of the entire sample as the product of all the individual likelihoods\(^9\) – Equation 4.6 (Cox, 1972).

---

8 Uniqueness of scrambled PNR was guarantee by ARC within a specific market

9 \(C_i\) is a censoring indicator equal to 0 for uncensored tickets and 1 for censored tickets
Furthermore, since the exact time of tickets transitioning from the state of “not-cancelled” to “cancelled” can be captured using a binary variable $y_{ij}$ equal with 1 if ticket is cancelled in the $j^{th}$ day from departure and 0 otherwise, it follows that Equation 4.7 is an alternative form to express the log-likelihood function. Moreover, the likelihood function for the entire sample (Equation 4.8) is equivalent with the likelihood function of a binary logistic regression model for which $y_{ij}$ are assumed to be a collection of independent variables and whose data structure is expanded\(^{10}\) to represent an unbalanced panel dataset (i.e., each ticket observation is replicated multiple times, one time for each day from departure of the ticket lifetime).

$$L = \prod_{i=1}^{n} \left[ h_i \prod_{j=1}^{k} (1-h_{ij}) \right] \cdot \left[ \prod_{j=1}^{k} (1-h_{ij}) \right]^{y_{ij}} \quad (4.6)$$

$$l = \log L = \sum_{i=1}^{n} \sum_{j=1}^{k} y_{ij} \cdot \log \left( \frac{h_{ij}}{1-h_{ij}} \right) + \sum_{i=1}^{n} \sum_{j=1}^{k} \log \left( 1-h_{ij} \right) \quad (4.7)$$

$$L = \prod_{i=1}^{n} \prod_{j=1}^{k} h_{ij}^{y_{ij}} (1-h_{ij})^{(1-y_{ij})} \quad (4.8)$$

The equivalence between the two likelihood formulations (Equations 4.6 and 4.8) defines the rationale behind the DTPO model, a model introduced by Cox (1972) and further detailed by several authors (e.g., Brown, 1975; Thompson, 1977). As a general characteristic, it is important to note that although the linearity in log-odds is similar to that of the binary logit model, the DTPO model predicts the conditional probabilities of failures at different times (i.e., there is a time-to-event process associated). Therefore, in contrast with the binary logit model designed to analyze cross-sectional datasets, the DTPO is designed to analyze longitudinal datasets. With respect to the DTPO model formulation Allison (1995) remarks its similarities with a Cox Proportional Hazards (PH) model. In fact, when the time-to-event dataset exhibits a significant number of tied events, the DTPO model is a very good alternative to the PH model. However, in contrast to the PH model the baseline hazard function\(^{11}\) for the DTPO has to be specified, a minor disadvantage when considering that any p.d.f. of the time-to-event can be approximated with a set of dummy variables. For a general set of covariates $X_i$, Equation 4.9 presents the general formulation of the DPTO model, while Equations 4.10 and 4.11 present how hazard and survival probability can be computed.

---

\(^{10}\) The creation of the expanded dataset process has several steps: (1) duplicating the set of time-invariant covariates over the entire life-time of a ticket, (2) filling in the time-variant covariates (if present) and (3) creating the binary indicators of the cancellation status $y_{ij}$

\(^{11}\) Baseline hazard function is equivalent with a model in which the sole predictor is the time and can be obtained by setting all other covariates to the reference point (usually 0)
\[
\log \left( \frac{h_{ij}}{1-h_{ij}} \right) = \Psi_{ij} + \beta_1 \cdot X_{y_1} + \beta_2 \cdot X_{y_2} + \ldots + \beta_l \cdot X_{y_l} 
\]

(4.9)

Where \( j=1,2,\ldots,k \) time intervals ; \( i=1,2,\ldots,n \) observations ; \( \Psi_{ij} \)- baseline hazard function

\[
h_{ij} = \frac{1}{1 + \exp(-\left( \Psi_{ij} + \beta_1 \cdot X_{y_1} + \beta_2 \cdot X_{y_2} + \ldots + \beta_l \cdot X_{y_l} \right))} 
\]

(4.10)

\[
S_{ij} = (1-h_{i1})(1-h_{i2})\ldots(1-h_{ik}) = \prod_{j=1}^{k} (1-h_{ij}) 
\]

(4.11)

5. Results

This section presents empirical results from the DTPO model. The choice of functional form for the baseline hazard, the impact of violation of the DTPO proportionality assumption on the pattern of conditional probabilities of cancellation (hazard), and the effect of the observed heterogeneity on this pattern are detailed.

With respect to the choice of functional form for the baseline hazard, it is important to note that the DTPO model estimation is constructed using two fundamental assumptions. First, a linear relation between the covariates and the logistic transformation of ticket cancellation hazard is assumed (linearity assumption). Second, the effect of covariates over the odds of cancellation is considered to be constant over time (proportionality assumption). Both aspects can be combined into an equivalent formulation of the DTPO model (Equation 4.12) which practically defines the multiplicative effect of the covariates log-linear function on a baseline odds function:

\[
\frac{h_{ij}}{1-h_{ij}} = \frac{h_{ij}^0}{1-h_{ij}^0} e^{\beta_1 \cdot X_{y_1} + \beta_2 \cdot X_{y_2} + \ldots + \beta_l \cdot X_{y_l}} 
\]

(4.12)

In the case when the magnitude of hazard probabilities is relatively small (i.e., ARC data), the Equation 4.12 is useful in generalizing the DTPO model to a proportional hazard (PH) model. Indeed, if conditional probabilities of canceling are small (\( h_{ij} \rightarrow \) small) the odds of a cancellation event will be approximately equal to the conditional probability of cancellation (i.e., \( h_{ij} \approx h_{ij} / (1-h_{ij}) \)). As a result, we can conceptualize the DTPO model as a close approximation of a proportional hazard (PH) model, and use this finding to motivate the “right” choice for the baseline hazard functional form. Figure 4 presents a comparison between the sample hazard profile\(^{12}\) of tickets cancellations and two\(^{13}\) of the three fitted baseline hazards functions, while Table 8 presents the coefficient estimates for all.

Although, the visual inspection of Figure 4 indicates that the second order polynomial is the only functional form to capture the “bath-tub” shape of the sample hazard profile, the lack of “cancellation” events for tickets booked 180 days form departure and more, makes this result questionable. At the expense of an increase in parsimony, the discrete baseline hazard formulation has the advantage of estimating the average cancellation rates over user-defined time

\(^{12}\) Generated as a bar plot of the sample hazard probabilities=proportion of tickets cancelling out of the tickets at risk

\(^{13}\) Although not showed, the Weibull baseline hazard specification had similar results with the discrete baseline hazard specification.
periods, periods that can be set up to reflect RM systems thresholds (e.g., advance purchase). Also, since covariates interactions with time are easier to interpret, the discrete baseline formulation is a convenient choice when studying possible derivations from the proportional odds assumption. In view of the two mentioned advantages, the discrete formulation was chosen to represent the base-line hazard function and, based on the advance purchase schema (see Table 9) a set of nine dummy variables was defined.

Once the functional form of baseline hazard is defined, the set of covariates was tested for possible violations of DTPO proportionality assumption\textsuperscript{14}. Since Time of Booking is the only covariate that violates this assumption (interactions between Time of Booking and Days from Departure (DFD) are significant - Table 9), the immediate implication on the cancellation process is that it is not memoryless. This finding is extremely important especially in view of methods currently applied in the forecast of cancellation rates/proportions. Specifically, it suggests that forecasting cancellation rates/proportions as extrapolations of previously realized values does not hold, as depending on the their Time of Booking passengers will exhibit different

\textsuperscript{14} Often enough in the survival analysis literature this step is ignored and possible violations attributed to the unobserved heterogeneity of covariates or simply ignored as the “average effect” over time captured by parameter estimates is considered to be valuable information. In the case of DTPO model, proportionality assumption was tested by including in the model estimation interactions between each covariate and the dummy variables defining the time-scale.
cancellation patterns. Still, before any generalization of this phenomenon can be extended to airline cancellation models (based on booking data), the impact of the distribution of cancellations not included in current analysis (booking churn) has to be studied as well.

The first three modes of Table 9 present the relative magnitude of parameter estimates for days from departure dummies \((DFDi)\), the time of booking \((TBooking)\), and the interactions between the two \((TB_{DFDi})\). \textit{Model1} specification captures only the influence of time, and indicates that relative to the reference time category \(([0-3)\) DFD), the hazard of canceling\(^{15}\) tickets decreases. With the inclusion of the time of booking in the set of covariates \((Model2)\), this “Weibull-like” pattern of the baseline hazard is further reshaped into a “bath-tub” pattern. As a result, the parameter estimates of days from departure categories exhibit a decreasing trend until the fifth category \(([30-45)\) DFD and increase afterwards. \textit{Model3} generalizes the results of \textit{Model2} and includes interactions between time of booking and days from departure, thus defining a family of different hazard curves one for each Time of Booking.

In order to illustrate the transformation of the baseline hazard function, using a set of predefined times of booking (14, 30, 60, 90, 180, and 330 days from departure), hazard predictions were generated and graphed for all three models (Figure 5). Visual inspection of Figure 5 proves that the \textit{Time of Booking} impact on the hazard of cancelling tickets is two-folded. First, the tickets which are booked early always have a lower hazard of being cancelled than those booked late. Secondly, depending on when the time of booking occurs, the shape of the hazard curve will be different. For example, tickets booked well in advance have the highest hazard of being cancelled close to the issue date followed by a slow decrease in time. In contrast, tickets booked moderately in advance exhibit the lowest hazard of being cancelled close to the issue date followed by an increase until the two-weeks prior to departure, from where the tickets hazard of being cancelled starts to decrease. Finally the hazard of being cancelled for tickets booked in the near proximity of departure increases as the departure date approaches.

\(^{15}\) This is possible because of the small values of probabilities which result in odds of cancellation hazard being equivalent with the cancellation hazard.
Figure 5: Baseline Hazard Profiles for different DTPO model specifications:
(a) Days from Departure only - Model1
(b) Days from Departure and Time of Booking – Model2
(c) Days from Departure, Time of Booking and Interactions – Model3

In order to assess how the effect of observed heterogeneity is distributed between different segmentations types, six more covariates were incorporated in the DTPO model. Since, the time
of booking was the only covariate to violate the assumption of proportionality, the family of hazard curves defined in previous paragraphs acts as a basis for influence of the rest of the covariates. The only difference is that, depending on the specific value of the covariate, the family of hazard curves will shift upwards or downwards with a factor approximately\(^{16}\) equal to the odds ratio estimate. Table 9 presents the estimation results for these six models (i.e., covariates effect is estimated sequentially- (4) Markets, (5) Group Size, (6) Length of Stay, (7) Outbound Departure Day of Week, (8) Carrier Groups, and (9) Fare Prorated by trip type).

With respect to the magnitude of the covariates effect relative to the family of hazard curves, the Likelihood Ratios (LR) tests of Table 9 enforce the idea that the most important determinants of cancellation behavior are Length of Stay (capturing one-ways vs. round-trips effect) followed by Group Size and Fare. Carrier groups, seasonality represented by the Outbound Departure Day of Week and Departure Month\(^{17}\), and Markets are also significant. Although, coefficient estimates across different specifications are relatively stable, model robustness needs to be further explored as exceptions exist (e.g., the instability of DFD2 and DFD9, dependence between Fare and Market).

The parameter estimates of Model4 to Model9 provide information on how the characteristics of the itinerary can impact the hazard of cancellation. These effects are incorporated assuming that they do not vary over time (although future research will explore the whether these covariates also vary with time). Most interesting, the group size odds-ratio estimates come to reinforce Thompson (1961) findings on the distribution of the cancellation rates across different groups. Indeed, all else being equal, the risk of cancelling for group tickets is lower than the risk of cancelling for individual tickets (only 40 to 50% percent). Moreover, as the group size increases to three or more, the risk of cancelling is further reduced (28 to 35%). Also, those outbound travel days that are historically associated with the start of business trips have higher cancellation rates. Specifically, relative to the reference day (Sunday) the parameter estimates for outbound departure day of the week show that the highest risk of cancelling is on Monday only to decrease until Friday when it starts to increases again.

A few results are counter-intuitive. Specifically, while round trip tickets with longer lengths of stay (associated with leisure travelers) are less likely to be cancelled than round trips with shorter the length of stay (associated with business travelers), overall, round trips have a higher risk of cancelling than one-ways trips. Given low cost carriers are not represented in the data, one may expect that one-way trips are more likely to be associated with business travelers and purchased closer to departure, and thus more likely to be cancelled than the round-trip tickets. However, an analysis of the data shows that one-way tickets are purchased throughout the booking horizon, and for some particular markets, are commonly purchased 30-45 days from departure. These one-way tickets may be “consolidator tickets” that are sold as part of a cruise package. Ticketing rules generally require these tickets be purchased 30-45 days in advance. Current discussions with ARC are underway to determine if the effect is due to the presence of consolidator bookings. However, if it is not possible to directly identify consolidator tickets, the model can

\(^{16}\) Again this statement is only valid for small values of the conditional probabilities of cancellation (hazard). General a constant factor change in odds does not correspond to a constant factor change in the probability.

\(^{17}\) Departure Month coefficient estimates were not significant.
be extended to distinguish between the effects of one-way tickets purchased more than 30 days in advance, and those purchased closer to departure.

Finally, while carrier and fare effects are included in the model, it is very difficult to provide a general interpretation of these effects based on the limited number of markets explored. Average fare is highly correlated with market, and different carriers may impose different refund and exchange ticketing policies. Current research is underway to further isolate the effect of carrier competition, fare, and carrier policy on cancellation behavior.
### Table 9: Discrete Time Proportional Odds Estimation Results for ARC Data

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>OR (z-stat)</td>
<td>OR (z-stat)</td>
<td>OR (z-stat)</td>
<td>OR (z-stat)</td>
<td>OR (z-stat)</td>
<td>OR (z-stat)</td>
<td>OR (z-stat)</td>
<td>OR (z-stat)</td>
<td>OR (z-stat)</td>
</tr>
<tr>
<td><strong>DFD2</strong></td>
<td>.807 (-1.45)</td>
<td>.845 (-3.25)</td>
<td>.88 (-1.60)**</td>
<td>.88 (-1.51)**</td>
<td>.88 (-1.59)**</td>
<td>.863 (-1.91)*</td>
<td>.854 (-2.06)*</td>
<td>.852 (-2.10)*</td>
</tr>
<tr>
<td><strong>DFD3</strong></td>
<td>.409 (-18.24)</td>
<td>.487 (-14.47)</td>
<td>.356 (-13.29)</td>
<td>.358 (-13.20)</td>
<td>.373 (-12.88)</td>
<td>.383 (-12.60)</td>
<td>.391 (-12.40)</td>
<td>.386 (-12.56)</td>
</tr>
<tr>
<td><strong>DFD4</strong></td>
<td>.245 (-20.59)</td>
<td>.348 (-14.97)</td>
<td>.188 (-13.20)</td>
<td>.189 (-13.15)</td>
<td>.212 (-12.43)</td>
<td>.231 (-11.76)</td>
<td>.243 (-11.42)</td>
<td>.238 (-11.60)</td>
</tr>
<tr>
<td><strong>DFD6</strong></td>
<td>.128 (-19.75)</td>
<td>.295 (-10.97)</td>
<td>.103 (-9.07)</td>
<td>.103 (-9.05)</td>
<td>.120 (-8.56)</td>
<td>.131 (-8.27)</td>
<td>.140 (-8.02)</td>
<td>.141 (-7.99)</td>
</tr>
<tr>
<td><strong>DFD7</strong></td>
<td>.117 (-20.69)</td>
<td>.384 (-8.09)</td>
<td>.069 (-8.56)</td>
<td>.069 (-8.56)</td>
<td>.107 (-8.08)</td>
<td>.121 (-7.66)</td>
<td>.132 (-7.38)</td>
<td>.133 (-7.33)</td>
</tr>
<tr>
<td><strong>DFD8</strong></td>
<td>.088 (-19.52)</td>
<td>.591 (-3.44)</td>
<td>.058 (-6.08)</td>
<td>.058 (-7.00)</td>
<td>.079 (-6.31)</td>
<td>.093 (-5.94)</td>
<td>.105 (-6.68)</td>
<td>.104 (-6.65)</td>
</tr>
<tr>
<td><strong>DFD9</strong></td>
<td>.073 (-8.55)</td>
<td>2.141 (2.21)</td>
<td>.342 (-9.55)</td>
<td>.351 (-9.53)</td>
<td>.555 (-9.30)</td>
<td>.706 (-1.18)</td>
<td>.850 (-0.08)</td>
<td>.855 (-0.08)</td>
</tr>
</tbody>
</table>

**Days of Departure (reference category “1”= 0-3 days)**

**Time of Booking and Interactions with Days from Departure**

**Markets (reference market=BoS/Mia)**

**Number of People in the Group (reference category = one person)**

**Length of Stay in Days (reference category = one way)**

**Outbound Departure Day of Week (reference day OutDOW=Sunday)**

**Carriers (reference category=dominant* carrier)**

**Fare (ProRated by TripType)**

### Models Statistics

- **LRch2(df)**: 1910.94 (8) 2475.95(9) 2668.41(17) 2800.70(24) 3299.52(26) 3930.31(31) 4070.13(37) 4224.47(41) 4610.64(42)
- **LR Test**: 565.01, 1, 0 192.46, 8, 0 132.29, 7, 0 498.82, 2, 0 630.79, 5, 0 139.83, 6, 0 154.33, 4, 0 386.18, 1, 0
- **Pseudo R**: 0.0319 0.0413 0.0445 0.0467 0.0551 0.0656 0.0679 0.0705 0.0769
- **LL**: -29067.02 -28725.41 -28629.18 -28563.04 -28313.63 -27998.237 -27928.324 -27851.157 -27658.067
- **No of obs**: 5044391 5044391 5044391 5044391 5044391 5044391 5044391 5044391 5044391

**Key**: * - Significant at 5% level; ** - Significant at 10% level; Bold – Not significant

- **DFD2** = 3 to 6 days; **DFD3** = 7 to 20 days; **DFD4** = 21 to 29 days; **DFD5** = 30 to 44 days; **DFD6** = 45 to 59 days;
- **DFD7** = 60 to 89 days **DFD8** =90 to 179 days; **DFD9** = more than 180 days
- **OutDOW2** =Monday; **OutDOW3** = Tuesday; ; **OutDOW6** = Saturday
- **Carriers codes were grouped across different markets according to similarities in their fare structure**

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*Note: The text above contains statistical data and analysis related to different models and variables, including odds ratios, z-statistics, and significance levels.*
6. Conclusions and Further Research

This study developed a model of airline passengers’ cancellation behavior based on a sample of ticketing data from the Airline Reporting Corporation. A Discrete Time Proportional Odds model showed that cancellation rates are influenced by both the time of booking and the time until departure. This is an important finding, because current cancellation models impose a “memoryless property” and assume the time of booking has no influence on cancellation rates. It indicates that forecasting cancellation rates based on historical averages may not capture the underlying mix of as depending on the their Time of Booking passengers will exhibit different cancellation patterns. In addition, the influence of many other covariates was explored. Aside from round-trip versus one-way tickets, empirical results were consistent with the hypothesis that business travelers, who are more apt to change travel plans, are more likely to refund or exchange tickets than leisure travelers.

Based on the results obtained with these eight markets, further research is planned to extend the results to 2005 departure and more markets. It is anticipated that the larger sample sizes will permit further refinement of how competition, carrier policy, and fare influences cancellation rates. Most interesting was the discovery that cancellation rates associated with purchased tickets are much lower than the rates associated with booking data. This suggests a large percentage of cancellations present in airline models may be due to “booking churn,” or the creation and removal of booking reservations (that have not been paid for) in carrier data. Current work is underway to see if voided ticket data (which are tickets that have been created but are “voided” prior to when payment is due) from ARC can be used to better understand the factors driving cancellation rates associated with booking churn.
References:


