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The Graduate School
The Smeal College of Business

EMPIRICAL MODELS FOR ORGANIZATIONAL SERVICE QUALITY DECISIONS

A Dissertation in
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by
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Abstract

In my dissertation, I explore how service quality decisions of firms are influenced by factors such as pricing decisions, market and firm characteristics, and competition. In essay I, I study the joint dynamic decisions of service quality and price. I also explicitly recognize that firms make service quality and pricing decisions in the presence of competitive forces (e.g., Steenkamp, Nijs, Hanssens and Dekimpe, 2005). Thus, I develop a model to capture the dynamic interplay among service quality (represented by flight delays), price, and performance outcomes (i.e., capacity utilization and demand) in the presence of potential competition (i.e., number of competitors, e.g., Mazzeo, 2003) and realized competition (i.e., actual competitive actions, e.g., Chandrashekar, Mehta, Chandrashekar and Grewal, 1999) for services firm. With the U.S. airline industry as the research context, I collect market (route) level, quarterly data from major firms (airlines) in those markets, and propose a structural vector autoregressive panel model. The results suggest interesting patterns of the asymmetry between service quality and price. In particular, though service quality decisions adjust to pricing decisions, pricing decisions are not adjusted to service quality decisions. Together with the result for competition variables, this finding indicates that firms adjust their prices primarily to manage capacity and in response to potential and realized competition. Service quality decisions instead reflect considerations of price, performance, and competitive factors. In essay II, I take a step further to explore how firms’ service quality decisions are influenced by competitors’ service quality decisions, market characteristics (i.e., potential demand), and firm characteristics (i.e., market power). I use both flight cancellations and flight delays as indicators of service quality. I apply the static game estimation method to correct for potential estimation bias from the endogeneity of competitors’ service decisions. The results suggest that flight cancellation and delay decisions are asymmetrically influenced by firm characteristics and competition. Specifically, flight cancellation decisions tend to be driven by firm characteristics related to cancellation costs and rescheduling convenience, while flight delay decisions are responsive to competition; in particular, firms tend to adjust their flight delay levels to differentiate their services from those of their competitors.
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Chapter 1

Introduction

In the service sector, such as airlines and hotels, it is critical for firms to improve the quality of their core products - services. Indeed, it is well established in service marketing literature that emphasis on service quality leads to many positive outcomes, such as increased customer satisfaction and customer retention rate. (e.g., Lariviere, 2008; Spreng and Mackoy, 1996; Zeithaml, Berry and Parasuraman, 1996). As service quality is critical for the success of service firms, it is reasonable to expect that service firms should lay heavy emphasis on service quality to provide the highest possible level of service quality. However, this conjecture seems to go against reality. In the airline industry, flight cancellations and delays are not uncommon. In the hotel industry, being short of staff seems not to be a rare problem. The inconsistency between what the literature suggests and what firms are actually doing aroused my interests in understanding how service firms determine their service quality levels, and what factors drive these decisions. I aim at answering these questions by my two dissertation essays.

The research topic of understanding firms’ service quality decisions is important for enriching the services marketing literature and providing managerial implication for services firms. Despite rich and in-depth research on how service quality drives potential firm performance outcomes, there are few studies treating the service quality as the outcome variable. Some studies discuss how firms may improve service quality by being market oriented (Raju and Lonial, 2001), formalizing the selling process, and/or applying a cross-functional team structure (Froehle, Roth, Chase and Voss, 2000). Previous research seems to suggest that firms should always improve their service quality. However, is it always profitable for firms to improve service quality? Is it possible that some firms strategically choose not to provide good services under certain market conditions? To answer these questions, we need to explicitly discuss how firms decide their service quality levels, which previous research has not explored. I believe this dissertation should contribute to services marketing literature by
providing new insights on the supply side of service quality. Findings from my dissertation should provide managerial implications for services firms. For instance, how should firms set service quality levels contingent upon price levels? Should firms improve service quality in markets where competition is intensive, as opposed to markets where competition is weak? Are all service dimensions symmetrically driven by the same set of factors? Conclusions from this dissertation should provide insights for firms on these issues.

One goal of most decisions of firms is to increase profits. Improving services on one hand, may expand revenue, but on the other hand may increase costs. The service quality decisions, therefore, are likely to depend on the expected profits, which are also determined by the price level. In essay I, I study the joint dynamic decisions of service quality and price, as both these decisions influence profits. I also explicitly recognize that firms make service quality and pricing decisions in the presence of competitive forces (e.g., Steenkamp et al., 2005). Thus, I develop a model to capture the dynamic interplay among service quality, price, and performance outcomes (i.e., capacity utilization and demand) in the presence of potential competition (i.e., number of competitors, e.g., Mazzeo, 2003) and realized competition (i.e., actual competitive actions, e.g., Chandrashekaran et al., 1999) for services firm. With the U.S. airline industry as the research context, I collect market (route) level, quarterly data from major firms (airlines) in those markets, and propose a structural vector autoregressive panel model. The results suggest interesting patterns of the asymmetry between service quality and price. In particular, though service quality decisions adjust to pricing decisions, pricing decisions are not adjusted to service quality decisions. Together with the result for competition variables, this finding indicates that firms adjust their prices primarily to manage capacity and in response to potential and realized competition. Service quality decisions instead reflect considerations of price, performance, and competitive factors. Results from my essay I show the importance of competition on firms’ service quality decisions.

Previous literature (e.g., Parasuraman, Zeithaml and Berry, 1988; Parasuraman, Zeithaml and Berry, 1991; Lariviere, 2008) also suggested the importance of treating service quality as a multi-dimensional construct. Therefore, in essay II, I take a step further to explore how firms’ service quality decisions are influenced by competitors’ service quality decisions, in addition to market characteristics (i.e., potential demand) and firm characteristics (i.e.,
market power). I use both percentage of flight cancellations and average flight delays to represent service quality. Firms may expect each other’s service quality decisions and choose their service levels accordingly. I thus apply the static game estimation method to correct for the potential estimation bias from the endogeneity of competitors’ service decisions as independent variables. The results suggest that flight cancellation and delay decisions are asymmetrically influenced by firm characteristics and competition. Specifically, flight cancellation decisions tend to be strongly driven by firm characteristics related to cancellation costs and rescheduling convenience, while flight delay decisions are strongly responsive to competition; in particular, firms tend to adjust their flight delay levels to either horizontally or vertically differentiate their services from those of their competitors.

The findings of both essays show that there are many factors potentially influence firms’ service quality decisions: these decisions are made contingent upon other marketing decisions, such as prices; service quality decisions are also constrained by performance outcomes, such as capacity management and demand; in addition, the service quality decision of a firm is also influenced by the intensity of market competition, as well as the competitors’ service performances. Therefore, it is not always feasible or optimal for firms to improve their services. These findings contribute to the service marketing literature by introducing contextual factors to the study of service quality. They also provide references for firms on how to decide service quality levels.
Chapter 2

Modeling Service Quality, Price, and Performance at the Market Level: The Role of Potential and Realized Competition

Abstract

For service firms, service quality and price are the two main strategic tools for effective competition. To capture the dynamic interplay among service quality, price, and performance outcomes, this study investigates competitive actions at the market level, using the U.S. airline industry and quarterly data about airlines competing in important markets (routes). The model features (1) a three-way data structure with variables varying across firms (airlines), markets, and time; (2) four endogenous variables – service quality (delays), price, and market-level performance measured by the number of passengers served and capacity utilization; (3) a vast number of markets (582 routes) and firms (seven airlines), such that the cross-sections of the data exceed the time dimensions (maximum 72 quarters); (4) exogenous competition and control variables; (5) dependence among markets, mainly caused by reciprocal routes; and (6) missing price information (11.41% of observations). The results of the structural vector autoregressive panel model offer evidence of cross-sectional dependence. Impulse response functions for statistical inference suggest that price decisions influence service quality decisions and performance outcomes; service quality decisions influence performance outcomes but not price decisions. Finally, service quality increases as realized competition (competitive action) increases, whereas price increases as either potential (number of competitors) or realized competition increase.
2.1. Introduction

Managing service firms in industries such as banking, hospitality, and airlines requires organizational decisions about the service quality (Mittal, Kamakura and Govind, 2004) and pricing (Pan, Ratchford and Shankar, 2002) levels that can best acquire and retain customers (Rust, Danaher and Varki, 2000). These decisions require some consideration of competitors’ actions too, such that they vary from one market to another. For example, the service quality and price offered in hotels depends on their locations and the intensity of competition in that area (Mazzeo, 2002); similarly, airlines often temporarily reduce fares and increase service quality on routes (markets) after low-cost carriers enter (Snider, 2009); Walmart’s effect on small retailers in geographically isolated markets also has been well documented (Ingram, Yue and Rao, 2010). With this article, I seek to develop a model that can capture the dynamic interplay among service quality, price, and performance outcomes, in the presence of such competitive actions at the market level.

With this proposition, I assert that the interplay between service quality and price plays out mainly at the market level. For example, hotels increase service quality and/or lower prices when the intensity of competition in their market increases (Mazzeo, 2002) and airlines exhibit similar behaviors in face of new entrants (Shepherd and Brock, 2009); at any given point in time, the levels of service quality and price vary across markets, together with the level of competition. The proposed time-series model at the firm and market levels thus entails a three-way (firm–market–time) data structure. Furthermore, because service quality and price might influence each other, and both variables should be influenced by and should influence performance, I also need a vector autoregressive (VAR) specification in which service quality, price, and market-level performance are endogenous and influence each other (Hamilton, 1994). The possibility that prices can be adjusted easily, in the presence of lagged effects, means that I also must allow for contemporaneous effects of price, which requires a structural VAR specification (Cooley and Dwyer, 1998).

Three additional issues also influence the model development and ability to address the research question. First, several firms compete in a market, and the number of competitors varies across markets and over time, such that I encounter a time-series, cross-sectional data
structure, for which panel models are appropriate (Baltagi, 2005). Typical panel models involve a single dependent variable and correct for endogeneity using instrumental variables (Arellano and Bond, 1991); however, I have multiple dependent variables (service quality, price, and performance) and thus need a panel structural VAR setup, as has appeared in some recent literature (Binder, Hsiao and Pesaran, 2005). Second, I recognize that the markets are interdependent; service quality and pricing decisions are interrelated across markets. Thus, I also seek to model cross-sectional dependence in the panel VAR framework (Huang, 2008). Third, to study the role of competition, I must note both potential (number of competitors) and realized (competitors’ actions) competition on service quality and price. Consistent with extant research (e.g., Steenkamp et al., 2005), I model service quality and price competition as exogenous, which results in a panel structural VARX model with cross-sectional dependence.

I test the model in the U.S. airline industry, for which both service quality and pricing decisions are critical—as effectively illustrated by two famous events. In what became popularly known as the “Valentine’s Day Massacre,” Jet Blue stranded nine planes on the tarmac at JFK Airport for more than six hours during a winter storm on February 14, 2007; this service failure represented a massive embarrassment for Jet Blue and a critical case study on service failures (Hoyt, O’Reilly, Rao and Sutton, 2010). In the “Mother of all Pricing Battles” in the summer of 1992, the U.S. airlines industry witnessed a brutal price war that, by some estimates, resulted in $1.53 billion in losses due to fare reductions (Morrison and Winston, 1996). In this setting, I define a market as a route from one city to another, and I collate data from multiple secondary sources to develop a model that can capture context idiosyncrasies, such as the cross-sectional dependencies that arise from reciprocal routes (i.e., the route from city A to city B is reciprocal to the route from city B to city A), as well as unique data challenges (e.g., missing price information). As I detail, the results from the panel VAR model indicate cross-sectional dependence; price decisions influence service quality decisions and performance outcomes, whereas service quality decisions influence performance outcomes but not price decisions. As we might expect, price is influenced positively by both potential and realized competition; however, service quality is negatively influenced by potential competition and positively influenced by realized competition. Consistent with extant research (Mazzeo, 2003; Rupp, Owens and Plumly, 2006), the potential
competition finding reverses in the cross-sectional analysis, which suggests the superiority of this model over cross-sectional models for studying service quality and competition in multimarket service contexts.

I organize the remainder of this article as follows: I begin by detailing my research context and data structure, and I provide model-free insights from the data. Next, I develop a model to capture the requisite elements of the data structure, followed by model estimation details. After I present the results, I conclude with implications and contributions of this study.

2.2. Research Context and Data

2.2.1 Research Setting

To study the interplay among service quality, price, and performance, I require a context in which both service quality and price are important decisions and longitudinal data about these important variables are available. Furthermore, considering my interest in modeling the effects of potential and realized competition related to service quality and price, firms should compete on both variables. Finally, to model competitive effects, I must be able to define competition at the market level and have access to competition data for both service quality and price variables.

The airline industry meets these criteria. In this service sector, service quality is important and has been widely studied (e.g., Grewal, Chandrashekar and Citrin, 2010). Pricing decisions also are critical for the success of airlines (Busse, 2002). Airlines compete in distinct markets (i.e., routes between cities; Snider 2009), so I can identify airlines that compete in each market and determine competition on both service quality (Mazzeo, 2003) and pricing (Gerardi and Shapiro, 2009). Overall, the airline industry is an appropriate context in which to model competitive interactions of service quality and pricing.

Currently the Airline Deregulation Act of 1978, which replaced the Civil Aeronautics Act of 1938, governs the U.S. airlines industry. The Airline Deregulation Act aims to encourage, develop, and maintain air transportation system by relaying on “actual and potential competition to provide efficiency, innovation, and low prices, and to determine the variety,
quality, and price of air transportation services” (Shepherd and Brock, 2009, p. 238). This quote from Shepherd and Brock (2009) uses language directly from the Airline Deregulation Act of 1978 and establishes the importance of price, service quality, and competition that from the crux of this research.

2.2.2 Data Structure and Measures

Market-level (i.e., route) data for the airline industry is published by the Bureau of Transportation Statistics (BTS). I pull my data from data sets published by the BTS and model the focal issues at the route level, which is the finest granularity of data available. Thus the three-way unbalanced panel features firm/airline \( f \), market route \( m \), and time \( t \); measured by quarter), such that \( P_{fmt} \) represents the price at which firm \( f \) serves market \( m \) at time \( t \). Not all firms serve all markets, and firms can enter and exit markets, so the dataset is unbalanced panel.

The BTS maintains data on all 25,163 U.S. markets, and I selected routes to study, according to the following criteria: (1) major airlines have a dominant market share, (2) the majority of passengers take direct flight (i.e., competition is less affected by connecting flights), and (3) the probability of missing price information is low (i.e., BTS collects price information for a random sample of 10% of itineraries, which creates the possibility of missing price data). I therefore collected data for markets of U.S. metropolitan statistical areas (MSAs) with populations of 2,500,000 or more, because these routes are more likely to satisfy my three criteria. The data pertain to direct routes between 21 cities (but 29 airports, because some MSAs have multiple airports, such as Chicago’s O’Hare and Midway), resulting in 582 markets.

In Table 2.1 I summarize the analysis variables, their sources, and any precedents in prior literature. Consistent with Mazzaro (2003), I use the percentage of flights delayed as the measure of service quality.\(^1\) I collect these data from the on-time performance dataset created

\(^1\)As Grewal et al. (2010) report, data on other measures of service quality, such as mishandled baggage and customer complaints, also are available at the firm level (but not at the firm-market level). For the firm level data, delay seems to load on the same latent factor as these other indicators (Grewal et al., 2010), so I use delay as the indicator of service quality at the firm-market level.
by the BTS, which contains departure delays (difference in minutes between scheduled and actual departure time), arrival delays (difference in minutes between scheduled and actual arrival time), cancellations, and diversions for each domestic flight operated by large carriers (i.e., that earn at least 1% of total revenue in the airline industry). This information is provided by the operating carrier (i.e., airline), as opposed to a ticketing or reporting carrier; so I assess all variables, including service quality and price, at the level of the individual airlines. In Figure 2.1 I provide a histogram for minutes of delay; consistent with Mazzeo (2003), I use 15 minutes or longer as a threshold to represent delay (i.e., cancelled flights are also included in the delay measure). For each quarter \(t\), I calculate delay as the percentage of flights by airline \(f\) delayed for 15 minutes or more in market \(m\), according to the scheduled arrival time.

Table 2.1: List of Variables

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<th>Variable Category</th>
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<td>Delay (service quality)</td>
<td>Price</td>
<td>Logit (\frac{\sum \text{ArrDelayedFlight}(&gt;15\text{min})}{\sum \text{Flight}})</td>
<td>OTP, BTS</td>
<td>Mazzeo (2003); Rupp et al. (2006)</td>
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<td>Competition</td>
<td>Capacity utilization</td>
<td></td>
<td>Logit (\frac{\sum \text{Passenger}}{\sum \text{Seat}})</td>
<td>T100, BTS</td>
<td>Snider (2009)</td>
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<tr>
<td>Competition</td>
<td>Number of passengers served</td>
<td>log(Passenger)</td>
<td></td>
<td>T100, BTS</td>
<td>Snider (2009)</td>
</tr>
<tr>
<td>Competition</td>
<td>Number of competitors at the airport level</td>
<td>(\sum \text{Carrier} - 1)</td>
<td></td>
<td>T100, BTS</td>
<td>Snider (2009)</td>
</tr>
<tr>
<td>Competition</td>
<td>Number of low cost competitors at the airport level</td>
<td>If focal carrier is a low cost carrier, (\sum \text{LowCostCarrier} - 1); If focal carrier is a full cost carrier, (\sum \text{LowCostCarrier});</td>
<td>T100, BTS</td>
<td>Snider (2009)</td>
<td></td>
</tr>
</tbody>
</table>
Number of competitors at the city level (not used in the estimation) If the focal carrier operates in another airport in the same MSA, \( \sum_{\text{Carrier}_{MSAlevel}} - 2 \); If the focal carrier does not operate in another airport in the same MSA, \( \sum_{\text{Carrier}_{MSAlevel}} - 1 \).

Number of low cost competitors at the city level (not used in the estimation) If the focal carrier is a low cost carrier, \( \sum_{\text{LowCostCarrier}_{MSAlevel}} - 1 \); If the focal carrier is not a low cost carrier, \( \sum_{\text{LowCostCarrier}_{MSAlevel}} \).

### Realized Competition

<table>
<thead>
<tr>
<th>Control Variables</th>
<th>Market Power</th>
<th>Network size</th>
<th>Multi-airport operations</th>
<th>Congestion Control of origin airport</th>
</tr>
</thead>
<tbody>
<tr>
<td>Competitor mean price</td>
<td>Given a route, ( \frac{\sum_{\text{carrier}} \text{price-carrier}}{\sum_{\text{carrier}} \text{delay-carrier}} )</td>
<td>DB1B, BTS</td>
<td>Pauwels (2004)</td>
<td></td>
</tr>
<tr>
<td>Competitor mean delay</td>
<td>( \frac{\sum_{\text{carrier}} \text{delay-carrier}}{\sum_{\text{carrier}} \text{delay-carrier}} )</td>
<td>OTP, BTS</td>
<td>Pauwels (2004)</td>
<td></td>
</tr>
<tr>
<td>Total number of flights departing from the same origin for the focal carrier</td>
<td>T100, BTS</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Total number of airports the focal carrier operates in the origin MSA-1</td>
<td>T100, BTS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total flights departure from the focal origin airport</td>
<td>T100, BTS</td>
<td>Mazzeo (2003); Rupp et al. (2006)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** I do not use congestion of destination because of its high correlation with congestion of origin (0.999). OTP stands for On-Time Performance.

I collect data on price from the origin and destination DB1B dataset produced by the BTS. Every quarter, this data set provides a 10% sampling of all domestic origin and destination itineraries, listing airline information (ticketing carrier, operating carrier, reporting carrier), number of connections, and itinerary price. I retain only the nonstop itineraries, to match price information with service quality information at the flight level. To avoid coding errors and bias due to frequent flier benefits, I follow Snider (2009) and retain only observations whose itinerary prices range from $50 to $5000. For each quarter, I take the average price of itineraries for each firm–market–quarter level, where the market is each origin—destination route combination. That is, each city pair provides two markets (Mazzeo, 2003):
flying from city A to B is one market, and from B to A is another. This market definition introduces dependencies across markets, which I correct for in the model specification.

To assess performance at the route level, I sought surrogates for the volume of business (i.e., demand) and capacity utilization, which determine airline profitability (e.g., Coelli, Grifell-Tatje and Perelman, 2002; Lecraw, 1978). I use the number of passengers served as an indicator of volume of business and percentage occupancy to instrument capacity utilization. The T100 Origin and Destination BTS database provides information about these performance metrics; it describes traffic for all domestic origins and destinations for carriers with annual revenues greater than $20 million.

2.2.2.1 Competition

I seek to model competition at the route level for both service quality and price; in addition to potential competition, or the impact of the number of competitors (Herfindhal index), I build on recent perspectives and model realized competition, or actual competitive actions (e.g., Chandrashekar et al., 1999; Sappington, 2003). Consistent with extant literature (Mazzeo, 2003; Rupp et al., 2006), I measure potential competition with the number of competitors and number of low cost competitors. I use distinct measures to assess realized

![Figure 2.1: Histogram for Minutes of Delay](image-url)
competition for service quality and price; for the former, I use the average percentage of delay by competitors in the same route and, for the latter, I use the average price of competitors on the same route.\textsuperscript{2}

\textbf{2.2.2.2 Control Variables}

Consistent with extant literature (Mazzeo, 2003; Rupp et al., 2006), I control for airport congestion factors when estimating the competition effects on flight delay. Because the correlation between origin airport congestion and destination airport congestion is fairly high ($\rho > .80$), I do not include a variable for destination airport congestion. In addition, market power, conceptualized as “the size of a carrier’s operations at the endpoints of the route” (Borenstein, 1989; Evans and Kessides, 1993), influences organizational strategic pricing decisions (Borenstein, 1989; Kim and Singal, 1993) and also should influence service quality decisions. On one hand, as a firm’s market power increases, service quality should decrease, because the firm can sell without emphasizing its service quality; on the other hand, for airlines, as market power increases, the firm takes a disproportionate amount of airport resources and thus might offer greater service quality. I use two variables to assess market power: network size (Borenstein, 1989; Morrison and Winston, 1996), equal to the number of flights departing from the origin airport, and multi-airport occupation (Levine, 2009), which is the number of origin airports that the focal airline serves in a MSA.\textsuperscript{3}

\textsuperscript{2}Because some large MSAs have more than one airport, carriers might face competition from other carriers that operate in the same city pair but different airports (though my route definition is airport specific, such that Midway to Seattle is a different route than O'Hare to Seattle). Each carrier also might operate in more than one airport in a MSA. Route-level competition variables correlate highly with city-level competition variables, and conceptually, I am interested in route (market)-level competition, so I only include market-level variables in the model.

\textsuperscript{3}Similar to extant research (e.g., Berry, Carnall and Spiller, 2006; Berry and Jia, 2010), I might have used a dummy variable to indicate if the origin airport is a hub for an airline; however, as I elaborate later, I needed to take a first difference to estimate the model, which would wipe out any dummy variable for the hub (i.e., I control for the hub airport). The network size of an airline typically increases if an airport is its hub; thus, network size provides a continuous measure of market power at the market/route level.
2.2.2.3 Missing Data

The DB1B dataset, from which I get information on prices, offers a 10% sampling of all domestic itineraries, and in these selected markets/routes, I find 11.41% (5,746 observations) with missing values; the missing price are not negligible (Little and Rubin, 1987). I contacted the person who manages the DB1B dataset to determine potential reasons for the missing price values, other than the random sampling error. First, some itineraries represent frequent fliers using their rewards to fly, in which case the price is recorded as $0 or nearly so. If I remove outliers (price data outside the $50–$5000 range; Snider 2009), I attain more complete price data. Second, bulk fares that airlines provide to travel agents provide airlines with no information about the price. As I detail in the next section, I use multiple imputation methods to estimate the missing values (Little and Rubin, 1987). Finally, in .09% (43) of the observations, information on delay, the measure of service quality, is missing. Because this missing information mainly comes from small airlines, I dropped these observations, because it is unlikely that excluding these cases would bias the estimation.

2.2.3 Descriptive Analysis

To gain further insights into the data, I carried out in-depth, univariate, descriptive analyses of the endogenous variables: service quality, price, number of passengers served, and capacity utilization (for descriptive statistics see Table 2.2 and Table 2.3). Service quality and capacity utilization both are measured on a [0,1] scale, so I logit transformed them to rescale the variables to a \((-\infty, +\infty)\) scale (Barnhart and Rosenstein, 1998; Cook and Weisberg, 1994). Price is always positive, so I also follow extant literature and log-transformed prices (Baltagi and Levin, 1986; Berry et al., 1995). Finally, to reduce the influence of outliers, I log-transformed the number of passengers served (Baltagi and Levin, 1986).

---

4 As more and more people join frequent flier programs, the chance of sampling customers using reward miles should increase over time. This intuition is confirmed; the percentage of missing data shows an increasing trend. The most missing price data occurred in 2003 (44% missing). There was not much variation in missing data across quarters, with a low of 10.56% in the third quarter and a high of 12.46% in the second quarter. In terms of airlines, the highest percentage of missing data referred to American Airlines (24.39%), and the lowest was for Southwest Airlines (3.23%).

5 As I report in Section 2.5.1., I assessed the accuracy of my imputation method using data from 1993 to 2002 for which there are no missing values; I obtained reasonable accuracy in imputing missing values.
Table 2.2: Descriptive Statistics and Bivariate Correlation Coefficients

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<tbody>
<tr>
<td>(1) Logit(delay)</td>
<td>1</td>
<td></td>
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<td>(2) Log(price)</td>
<td>.089 ‡</td>
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<tr>
<td>(3) Logit(capacity utilization)</td>
<td>.036 ‡</td>
<td>.087 ‡</td>
<td>1</td>
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<tr>
<td>(4) Log(number of passengers served)</td>
<td>.121 ‡</td>
<td>-.026 ‡</td>
<td>.333 ‡</td>
<td>1</td>
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<tr>
<td>(5) Log(Price) (t-1)</td>
<td>.082 ‡</td>
<td>.869 ‡</td>
<td>.090 ‡</td>
<td>-.031 ‡</td>
<td>1</td>
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<tr>
<td>(6) Logit(delay(t-1))</td>
<td>.628 ‡</td>
<td>.083 ‡</td>
<td>.042 ‡</td>
<td>.124 ‡</td>
<td>.089 ‡</td>
<td>1</td>
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<tr>
<td>(7) Logit(capacity utilization (t-1))</td>
<td>.030 ‡</td>
<td>.097 ‡</td>
<td>.812 ‡</td>
<td>.276 ‡</td>
<td>.080 ‡</td>
<td>.038 ‡</td>
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<tr>
<td>(8) Log(number of passengers served (t-1))</td>
<td>.125 ‡</td>
<td>-.029 ‡</td>
<td>.266 ‡</td>
<td>.960 ‡</td>
<td>-.036 ‡</td>
<td>.117 ‡</td>
<td>.319 ‡</td>
<td>1</td>
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<tr>
<td>(9) Competitor mean price</td>
<td>.052 ‡</td>
<td>.559 ‡</td>
<td>.001</td>
<td>-.115 ‡</td>
<td>.540 ‡</td>
<td>.041 ‡</td>
<td>.001</td>
<td>-.119 ‡</td>
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<tr>
<td>(10) Competitor mean delay</td>
<td>.428 ‡</td>
<td>.063 ‡</td>
<td>.011 ‡</td>
<td>.027 ‡</td>
<td>.055 ‡</td>
<td>.287 ‡</td>
<td>.012 ‡</td>
<td>.034 ‡</td>
<td>.059 ‡</td>
<td>1</td>
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‡ p < 0.01. † p < 0.05.
Table 2.3: Descriptive Statistics and Bivariate Correlation Coefficients (continued)

<table>
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<tbody>
<tr>
<td>(11) Number of competitors</td>
<td>.063‡</td>
<td>-.306‡</td>
<td>-.044‡</td>
<td>-.059‡</td>
<td>-.300‡</td>
<td>.062‡</td>
<td>-.046‡</td>
<td>-.073‡</td>
<td>-.212‡</td>
<td>.055‡</td>
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<tr>
<td>(12) Number of low cost competitors</td>
<td>-.027‡</td>
<td>-.197‡</td>
<td>.210‡</td>
<td>.128‡</td>
<td>-.188‡</td>
<td>-.022‡</td>
<td>.208‡</td>
<td>-.189‡</td>
<td>-.027‡</td>
<td>.402‡</td>
<td>1</td>
<td></td>
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<tr>
<td>(13) Multi-airport operation</td>
<td>.140‡</td>
<td>.102‡</td>
<td>-.060‡</td>
<td>.096‡</td>
<td>.104‡</td>
<td>.141‡</td>
<td>-.061‡</td>
<td>.100‡</td>
<td>.045‡</td>
<td>.128‡</td>
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<td>-.078‡</td>
<td>1</td>
<td></td>
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<tr>
<td>(14) Network size</td>
<td>.225‡</td>
<td>.063‡</td>
<td>.064‡</td>
<td>.286‡</td>
<td>.062‡</td>
<td>.232‡</td>
<td>.057‡</td>
<td>.281‡</td>
<td>-.028‡</td>
<td>.128‡</td>
<td>-.041‡</td>
<td>-.005</td>
<td>.066‡</td>
<td>1</td>
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<tr>
<td>(15) Congestion origin</td>
<td>.168‡</td>
<td>.038‡</td>
<td>.070†</td>
<td>.254‡</td>
<td>.040‡</td>
<td>.176‡</td>
<td>.055‡</td>
<td>.250‡</td>
<td>-.028‡</td>
<td>.125‡</td>
<td>.236‡</td>
<td>.100‡</td>
<td>-.007</td>
<td>.540‡</td>
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<tr>
<td>(16) Number of competitors at city level</td>
<td>.143‡</td>
<td>-.295‡</td>
<td>-.108‡</td>
<td>.059‡</td>
<td>-.291‡</td>
<td>.141‡</td>
<td>-.109‡</td>
<td>.074‡</td>
<td>-.159‡</td>
<td>.177‡</td>
<td>.671‡</td>
<td>.161‡</td>
<td>.275‡</td>
<td>-.059‡</td>
<td>.142‡</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>(17) Number of low cost competitors at city level</td>
<td>.069‡</td>
<td>-.207‡</td>
<td>.208‡</td>
<td>.205‡</td>
<td>-.201‡</td>
<td>.075‡</td>
<td>.203‡</td>
<td>-.211‡</td>
<td>-.171‡</td>
<td>.091‡</td>
<td>.385‡</td>
<td>.691‡</td>
<td>.080‡</td>
<td>.025‡</td>
<td>.237‡</td>
<td>.447‡</td>
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<tr>
<td>(19) Congestion at destination</td>
<td>.168‡</td>
<td>.038‡</td>
<td>.069‡</td>
<td>.254‡</td>
<td>.040‡</td>
<td>.176‡</td>
<td>.055‡</td>
<td>.250‡</td>
<td>-.028‡</td>
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<td>.100‡</td>
<td>-.007</td>
<td>.589‡</td>
<td>.999‡</td>
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<td>.238‡</td>
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<tr>
<td>Mean</td>
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<td>.953</td>
<td>1.52</td>
<td>5.28</td>
<td>-1.287</td>
<td>.953</td>
<td>1.55</td>
<td>20.74</td>
<td>.22</td>
<td>2.01</td>
<td>.32</td>
<td>.26</td>
<td>9.596</td>
<td>33.510</td>
<td>3.72</td>
<td>.65</td>
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<tr>
<td>Standard deviation</td>
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<td>.47</td>
<td>.691</td>
<td>.863</td>
<td>.47</td>
<td>.594</td>
<td>.681</td>
<td>.839</td>
<td>97.72</td>
<td>.096</td>
<td>1.78</td>
<td>.57</td>
<td>.54</td>
<td>9.888</td>
<td>15.597</td>
<td>3.33</td>
<td>.85</td>
</tr>
</tbody>
</table>

‡ p < 0.01. † p < 0.05.
Figure 2.2: Time Variation in Service Quality and Price for Select Routes
To provide insights into service quality and price at the route level, I present longitudinal plots in Figure 2.2; each line represents an airline serving a particular route. The data in Figure 2.2 related to service quality suggest that (1) the level of service quality provided by each airline varies over time; (2) in each given market, there is considerable variability in service quality across airlines; (3) the average level of service quality varies across markets; and (4) if we were to rank airlines on service quality, that ranking also varies across markets and over time. Similar conclusions emerge for price from the plots in Figure 2.2, except that the price fluctuations are much higher than the service quality fluctuations (perhaps because price is much easier to change).

Scrutiny of data on number of passengers shows seasonal variation; however, there also is stickiness such that airlines that serve more passengers continue to do so over time. For capacity utilization I find considerable variation in the capacity utilization rankings of airlines; for some markets, the level of capacity utilization varies over time, whereas in others, it remains fairly stable (plots for number of passengers served and capacity utilization are available in supplementary document). Such variations support my efforts to develop a market-level model.

2.3. Model Specification

I seek to develop a model that captures the interplay of service quality, price, and two performance metrics (number of passengers served and capacity utilization) at the market level. With the longitudinal micro-data about airlines serving various markets, I also seek to assess the impacts of competition on service quality and on price. I highlight six key features of the data structure and the ensuing model specification: (1) in the three-way structure, all variables vary across firms (airlines) and markets (routes) and over time; (2) there are four endogenous variables—service quality (delay), price, number of passengers served, and capacity utilization, (3) the large number of markets (582 routes) and firms (seven airlines)\(^6\)

\(^6\)The seven airlines are American, Continental, Delta, Northwestern, United, US Airways, and Southwest Airlines. They are the top airlines by revenue in the United States, and their performances have been tracked constantly by the BTS.
means that the cross-sectional data dimensions exceed the time dimensions (72 quarters); (4) I have exogenous competition and control variables; (5) there is dependence among markets, mainly due to reciprocal routes; and (6) price information is missing (11.41% observations).

My model incorporates all these data features. First, two-way data structures are common in marketing and economics (e.g., firms over time), whereas three-way data structures appear more often in gravity models in international economics (Bergstrand, 1985; Egger, 2000), where it is important to specify the requisite heterogeneity for the intercept term; I delve into this issue in the next section. Second, because I have four endogenous variables for every route and airline combination, I need some type of vector autoregression (VAR) framework. Third, the large cross-section, exceeding even the time series, requires panel data models (Baltagi, 2005). Typical panel models have only one dependent endogenous variable,\textsuperscript{7} whereas I have four, so I turn to research on panel data to develop a panel VAR (PVAR) specification (e.g., Holtz-Eakin, Newey and Rosen, 1987; Love and Zicchino, 2006). Fourth, I explicitly model cross-sectional dependence in the error structure that arises from reciprocal routes (e.g., Ahn and Schmidt, 1995; Huang, 2008; Mutl, 2009). Fifth, I discuss the missing data mechanism and take appropriate measures to account for missing values (Little and Rubin, 1987).

2.3.1 Three-Way Data

Most prominent panel data in marketing and economics are two-way, such as data on firms over time, and the methods to model such data structures are well documented (e.g., Baltagi, 2005). Three-way panel data structure instead tends to appear in gravity models in international economics, to model interactions among exporting and importing countries over time (Bergstrand, 1985; Egger, 2000). Related literature suggests that it is critical to model heterogeneity in the three sources and any potential interactions (Baltagi, Egger and Pfaffermayr, 2003). The data structure involves a three-way panel, for which each observa-

\textsuperscript{7}Although there are methods to correct for the endogeneity of explanatory variables (e.g., Ahn and Schmidt, 1995; Arellano and Bond, 1991; Hsiao, Pesaran and Tahmiscioglu, 2002), my goal is to study the interplay among service quality, price, and performance metrics, requiring contemporaneous and effects; thus, a panel VAR approach is more appropriate than just correcting for endogeneity.
tion is a unique combination of firm–market–time. Consistent with gravity models literature (Egger and Pfäffermayr, 2003), I must include a fixed effect for each individual observation in time, which represents the unique combination of firm and market. Thus, I include fixed effects for each firm, each market, and each firm–market combination (a similar fixed effect structure appears in PVAR models, as I discuss subsequently; Binder et al. (2005) and Holtz-Eakin, Newey and Rosen (1988)). This formulation can account for any firm effects, such as brand equity or idiosyncratic offerings (e.g., frequent flyer program features); any effects due to the markets, such as congestion airports; and any effects due to firm–market combinations, such as the significance of the route for the airline. I also include time-specific fixed effects for each quarter (Baltagi, 2005; Egger and Pfäffermayr, 2003), which should account for any time-specific incidents (e.g., the 9/11 terrorist attacks). Mathematically, the fixed effects can be summarized as:

$$y_{fmt} = \alpha_{1t} + \alpha_{2f} + \alpha_{3m} + \alpha_{4fm} + \mu_{fmt},$$  \hspace{1cm} (2.1)$$

where $y_{fmt}$ is the vector of the four endogenous variables pertaining to firm ($f$) in market ($m$) at time ($t$), $\alpha_{1t}$ denote the time-specific dummy variables, $\alpha_{2f}$ are firm-specific dummy variables, $\alpha_{3m}$ are market-specific dummy variables, $\alpha_{4fm}$ are firm–market-specific fixed effects, and $\mu_{fmt}$ is the residual of firm $f$ in market $m$ at time $t$.

### 2.4. VAR Specification

For a given firm–market–time combination, I model four endogenous variables, whose lagged terms also influence one another. Among these four endogenous variables, I expect a pattern of contemporaneous effects that can capture the pattern of effects in the current time period. That is, I expect contemporaneous and lagged effects among endogenous variables and therefore use a structural VAR specification (Cooley and Dwyer, 1998; Enders, 2004):
\[
A \times \begin{bmatrix}
SQ_t \\
P_t \\
PS_t \\
CapU_t
\end{bmatrix} = \begin{bmatrix}
\sum_{c=1}^{C} \delta_{sq}^{c} \text{Comp}_{c,t} + \sum_{CON}^{\text{CON}} \gamma_{sq}^{\text{Control}_{con},t} \\
\sum_{c=1}^{C} \delta_{p}^{c} \text{Comp}_{c,t} + \sum_{CON}^{\text{CON}} \gamma_{p}^{\text{Control}_{con},t} \\
\sum_{c=1}^{C} \delta_{ps}^{c} \text{Comp}_{c,t} + \sum_{CON}^{\text{CON}} \gamma_{ps}^{\text{Control}_{con},t} \\
\sum_{c=1}^{C} \delta_{u}^{c} \text{Comp}_{c,t} + \sum_{CON}^{\text{CON}} \gamma_{u}^{\text{Control}_{con},t}
\end{bmatrix}
\]

(2.2)

\[
+ \sum_{\kappa=1}^{K} \begin{bmatrix}
\beta_{11}^{\kappa} & \beta_{12}^{\kappa} & \beta_{13}^{\kappa} & \beta_{14}^{\kappa} \\
\beta_{21}^{\kappa} & \beta_{22}^{\kappa} & \beta_{23}^{\kappa} & \beta_{24}^{\kappa} \\
\beta_{31}^{\kappa} & \beta_{32}^{\kappa} & \beta_{33}^{\kappa} & \beta_{34}^{\kappa} \\
\beta_{41}^{\kappa} & \beta_{42}^{\kappa} & \beta_{43}^{\kappa} & \beta_{44}^{\kappa}
\end{bmatrix} \times \begin{bmatrix}
SQ_{t-k} \\
P_{t-k} \\
PS_{t-k} \\
CapU_{t-k}
\end{bmatrix} \begin{bmatrix}
\mu_{sq,t} \\
\mu_{p,t} \\
\mu_{ps,t} \\
\mu_{u,t}
\end{bmatrix},
\]

where

\[
A = \begin{bmatrix}
1 & 0 & 0 & -\beta_{14}^{0} \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & -\beta_{33}^{0} & 1
\end{bmatrix}
\]

\[\{SQ_t, P_t, PS_t, CapU_t\}^t\] is the vector of endogenous variables (logit of delay, log of price, log of number of passengers served, logit of capacity utilization) at time \(t\); \(K\) denotes the number of lags; \(\text{Comp}_{c,t}\) is an \(1 \times 4\) vector of all competition variables (number of competitors, number of low cost competitors, competitor mean delay, competitor mean price); \(\text{Control}_{con,t}\) is an \(1 \times 4\) vector of the control variables (traffic cost, congestion of origin, network size, multi-airport operation); and \([\mu_{sq,t}, \mu_{p,t}, \mu_{ps,t}, \mu_{u,t}]^t \sim N(0, \Sigma)\).

I multiply the vector of endogenous variables by the matrix \(A\) to account for potential contemporaneous effects. Specifically,

1. Because demand is sensitive to immediate price, price should have a contemporaneous effect on the number of passengers served (I expect a negative effect: as price increases, the number of passengers decreases).

2. The number of passengers served should influence capacity utilization, because airlines adjust their capacity on the basis of anticipated demand (I predict a negative effect but acknowledge the difficulty of making an accurate prediction).
3. Service quality might depend on capacity utilization, because the boarding time and flight attendants per customer vary with the number of passengers on a flight (I expect a negative effect: as capacity utilization increases, service quality decreases).

2.4.1 Panel VAR Model

In most marketing applications of VAR, the estimated models (e.g., Pauwels, Hanssens and Siddarth, 2002; Srinivasan, Leszczyc and Bass, 2000) exhibit long time series and small cross-sectional units (large T, small N). Yet the data comprise 582 markets, seven airlines (or 1,263 cross-sectional elements), but at most 72 quarters of time for each airline–market combination. In other words, I have large cross-section units and short time series (small T, large N), which makes it difficult, and perhaps meaningless, to perform several thousands of conventional VAR estimations. To make full use of the data, I instead estimate a PVAR model (Holtz-Eakin et al., 1988; Love and Zicchino, 2006) and estimate the coefficients by pooling all data, even as I control for individual effects at different levels. Thus, I combine Equations 2.1 and 2.2 and write the PVAR model as follows (this specification poses unique estimation challenges that I discuss in the next section; in Equation 2.3, the subscripts $sq$, $p$, $ps$, and $u$ refer to service quality, price, number of passengers served, and capacity utilization, respectively):
\[
\begin{bmatrix}
1 & 0 & 0 & -\beta_{14}^0 \\
0 & 1 & 0 & 0 \\
0 & -\beta_{32}^0 & 1 & 0 \\
0 & 0 & -\beta_{43}^0 & 1
\end{bmatrix}
\begin{bmatrix}
SQ_t \\
P_t \\
PS_t \\
CapU_t
\end{bmatrix}
= \begin{bmatrix}
\alpha_{1sq} + \alpha_{2sq} + \alpha_{3sqm} + \alpha_{4sqf} \\
\alpha_{1pt} + \alpha_{2pf} + \alpha_{3pm} + \alpha_{4pf} \\
\alpha_{1pst} + \alpha_{2psf} + \alpha_{3psm} + \alpha_{4psf} \\
\alpha_{1ut} + \alpha_{2uf} + \alpha_{3um} + \alpha_{4uf}
\end{bmatrix}
\]

\[
\sum_{c=1}^{C} \delta_{sq}^c \text{Comp}_{c,t} + \sum_{\text{CON}_{con}=1}^{\text{CON}} \gamma_{sq}^{\text{con}} \text{Control}_{con,t}
\]

\[
\sum_{c=1}^{C} \delta_{pf}^c \text{Comp}_{c,t} + \sum_{\text{CON}_{con}=1}^{\text{CON}} \gamma_{pf}^{\text{con}} \text{Control}_{con,t}
\]

\[
\sum_{c=1}^{C} \delta_{ps}^c \text{Comp}_{c,t} + \sum_{\text{CON}_{con}=1}^{\text{CON}} \gamma_{ps}^{\text{con}} \text{Control}_{con,t}
\]

\[
\sum_{c=1}^{C} \delta_{pu}^c \text{Comp}_{c,t} + \sum_{\text{CON}_{con}=1}^{\text{CON}} \gamma_{pu}^{\text{con}} \text{Control}_{con,t}
\]

\[
+ \sum_{\kappa=1}^{K} \begin{bmatrix}
\beta_{11}^\kappa & \beta_{12}^\kappa & \beta_{13}^\kappa & \beta_{14}^\kappa \\
\beta_{21}^\kappa & \beta_{22}^\kappa & \beta_{23}^\kappa & \beta_{24}^\kappa \\
\beta_{31}^\kappa & \beta_{32}^\kappa & \beta_{33}^\kappa & \beta_{34}^\kappa \\
\beta_{41}^\kappa & \beta_{42}^\kappa & \beta_{43}^\kappa & \beta_{44}^\kappa
\end{bmatrix}
\begin{bmatrix}
SQ_{t-\kappa} \\
P_{t-\kappa} \\
PS_{t-\kappa} \\
CapU_{t-\kappa}
\end{bmatrix}
+ \begin{bmatrix}
\mu_{sq,t} \\
\mu_{pt,t} \\
\mu_{ps,t} \\
\mu_{ut,t}
\end{bmatrix}
\]

\[
(2.3)
\]

2.4.2 Cross-Sectional Dependence

I treat each unique combination of origin–destination airport pairs as a market. Because consumers usually buy round-trip tickets when they travel, they likely consider price and service quality for both the route and its reciprocal route. Thus, airlines must jointly determine their price and service quality levels, as well as how much flight capacity to provide for the two routes (city A to city B and its reciprocal, city B to city A). For each airline–time combination, the price, service quality, capacity utilization, and number of passenger served are not independent of these same variables in connection to the reciprocal route. Instead, price, service quality, capacity utilization, and the number of passenger served are functions of the reciprocal route versions of those variables. I model this cross-sectional dependency
in a panel setting with the following equation (Huang, 2008; Mutl, 2009):

\[
\begin{bmatrix}
1 & 0 & 0 & -\beta_{14}^0 \\
0 & 1 & 0 & 0 \\
0 & -\beta_{32}^0 & 1 & 0 \\
0 & 0 & -\beta_{43}^0 & 1
\end{bmatrix}
\begin{bmatrix}
SQ_{fbat} \\
P_{fbat} \\
PS_{fbat} \\
CapU_{fbat}
\end{bmatrix}
= 
\begin{bmatrix}
\alpha_{1sq} + \alpha_{2sq} + \alpha_{3sqab} + \alpha_{4sqf} \\
\alpha_{1pt} + \alpha_{2pf} + \alpha_{3pab} + \alpha_{4pf} \\
\alpha_{1pst} + \alpha_{2psf} + \alpha_{3psab} + \alpha_{4psf} \\
\alpha_{1ut} + \alpha_{2uf} + \alpha_{3uab} + \alpha_{4uf}
\end{bmatrix}
\]

\[
S_{ij} + \eta_p
\begin{bmatrix}
\eta_{sq} & 0 & 0 & 0 \\
0 & \eta_p & 0 & 0 \\
0 & 0 & \eta_{ps} & 0 \\
0 & 0 & 0 & \eta_u
\end{bmatrix}
\begin{bmatrix}
SQ_{fbat} \\
P_{fbat} \\
PS_{fbat} \\
CapU_{fbat}
\end{bmatrix}
+ 
\sum_{\kappa=1}^{K} \left[ \begin{bmatrix}
\beta_{11}^\kappa & \beta_{12}^\kappa & \beta_{13}^\kappa & \beta_{14}^\kappa \\
\beta_{21}^\kappa & \beta_{22}^\kappa & \beta_{23}^\kappa & \beta_{24}^\kappa \\
\beta_{31}^\kappa & \beta_{32}^\kappa & \beta_{33}^\kappa & \beta_{34}^\kappa \\
\beta_{41}^\kappa & \beta_{42}^\kappa & \beta_{43}^\kappa & \beta_{44}^\kappa
\end{bmatrix}ight]
\begin{bmatrix}
\mu_{sq, fbat} \\
\mu_{p, fbat} \\
\mu_{ps, fbat} \\
\mu_{u, fbat}
\end{bmatrix}
\]

\[
\begin{bmatrix}
C \\
C \\
C \\
C
\end{bmatrix}
\sum_{c=1}^{C} \delta^c_{sq} Comp_{c,fbat} + 
\sum_{c=1}^{C} \delta^c_{p} Comp_{c,fbat} + 
\sum_{c=1}^{C} \delta^c_{ps} Comp_{c,fbat} + 
\sum_{c=1}^{C} \delta^c_{u} Comp_{c,fbat}
\]

where \(\eta\) are the coefficients of the endogenous variables in the paired market. For ease of presentation, I distinguish the market subscript into \(ab\), such that \(a\) indicates the origin airport, and \(b\) stands for the destination airport.

### 2.4.3 Missing Data

I sought the best possible approach to manage the missing price data. Consistent with extant literature (Little and Rubin, 1987; Schafer, 1997), I first attempted to understand whether the mechanism entailed missing completely at random (MCAR), missing at random (MAR), or not missing at random (NMAR) (Rubin, 1976). I follow conventions and denote \(Y = (y_{ij})\) as the data matrix, such that \(Y_{obs}\) represents the observed component, and \(Y_{mis}\) is the missing component; in the missing data indicator matrix \(M = (m_{ij})\), \(m_{ij} = 1\) if \(y_{ij}\) is missing and \(m_{ij} = 0\) if \(y_{ij}\) is present. The missing data mechanism (MCAR, MAR, or NMAR) is defined as the conditional distribution of \(M\) given \(Y\), such that \(f(M|Y, \phi)\) where \(\phi\) denotes unknown parameters, I determine that (1) MCAR implies that missing data do not
depend on the value of the data, missing or observed, such that \( f(M|Y, \phi) = f(M|\phi) \forall Y, \phi \); (2) MAR makes a less restrictive assumption, and missing data depend only on the \( Y_{obs} \) component, not the \( Y_{mis} \) component, or \( f(M|Y, \phi) = f(M|Y_{obs}, \phi) \forall Y_{mis}, \phi \); and (3) NMAR is critical when \( M \) depends on \( Y_{mis} \) (Little and Rubin, 1987; Schafer, 1997).

In the dataset, the missing data pertain only to prices and appear largely the result of frequent flier programs and bulk fares. Thus, the missing data do not relate to the price of the ticket (NMAR is irrelevant), and observed data \( Y_{obs} \) are informative about the missing data \( Y_{mis} \), because they come from the same airline, market (route), and/or time (MCAR is too restrictive). Thus, MAR provides the most appropriate missing data mechanism.

If \( \theta \) denotes the parameters for the data generation process for \( Y = (Y_{obs}, Y_{mis}) \), then with an MAR assumption, I can write the joint probability of \( \eta = (\theta, \phi) \) as:

\[
Pr[\theta, \phi|Y_{obs}, M] \propto Pr[M, Y_{obs}|\theta, \phi] \pi(\theta, \phi) \propto Pr[M|Y_{obs}, \phi] Pr[Y_{obs}|\theta] \pi(\theta, \phi)
\]  

(2.5)

where \( \pi(\theta, \phi) \) is the joint prior distribution. Assuming independent priors for \( \theta \) and \( \phi \), I also can rewrite Equation 2.5 as:

\[
Pr[\theta, \phi|Y_{obs}, M] \propto Pr[M|Y_{obs}, \phi] Pr[Y_{obs}|\theta] \pi_{\theta}(\theta) \pi_{\phi}(\phi)
\]  

(2.6)

Because I seek statistical inferences about \( \theta \), I derive the marginal posterior for \( \theta \) by integrating out \( \phi \) from Equation 2.6, which provides:

\[
Pr[\theta|Y_{obs}, M] = \int Pr[\theta, \phi|Y_{obs}, M] d\phi \propto Pr[Y_{obs}|\theta] \pi_{\theta}(\theta) \int Pr[M|Y_{obs}, \phi] \pi_{\phi}(\phi) d\phi
\]  

(2.7)

The integral on the right-hand side of the equation does not depend on \( \theta \), so I rewrite Equation 2.7 as follows:

\[
Pr[\theta|Y_{obs}, M] = L[\theta|Y_{obs}] \pi_{\phi}(\phi).
\]  

(2.8)

Finally, because the inference of \( \theta \) does not depend on \( \phi \), I resort to data imputation for the missing values and draw inferences of \( \theta \) (Little and Rubin, 1987; Schafer, 1997); I provide the details of this imputation in the next section.
2.5. Model Estimation

To estimate the model, I first use unit-root tests of stationarity in the endogenous variables, then apply the Akaike (AIC) and Bayesian (BIC) information criteria to determine the number of lags for the endogenous variables in the PVARX system. Next, I impute the missing price values, apply a first difference to eliminate the individual effect (Anderson and Hsiao, 1982; Holtz-Eakin et al., 1988), correct for cross-sectional dependence between each pair of markets, and modify the three-step estimation procedure suggested by Holtz-Eakin et al. (1987) to account for the unbalanced panel structure in the data.

2.5.1 Unit Root Tests

I apply Choi’s (2001) test statistics to the four endogenous variables (logit of delay, log of price, logit of capacity utilization, and log of number of passenger served) to determine the potential presence of unit roots. For each variable $y$, I apply the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) to each time series (i.e., firm—market combination; see Equation 2.9), then derive the Choi (2001) test statistics (Equation 2.10):

$$
\Delta y_t = \alpha_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \epsilon_t \tag{2.9}
$$

$$
Z = \frac{1}{\sqrt{FM}} \sum_{fm=1}^{FM} \Phi^{-1}(p_{fm}) \tag{2.10}
$$

where $FM$ is the total number of firm–market combinations, $\Phi(\cdot)$ is the standard normal cumulative distribution function, and $p_{fm}$ is the asymptotic $p$ value for the ADF test for each time series.

If $Z$ is less than the critical value of the lower tail of the standard normal distribution, I reject the null hypothesis that all the time series are unit root non-stationary (Hoffman, Lee, Ramasamy and Yeung, 2005). I perform this Choi test independently for each of the four endogenous variables to determine the presence of unit roots.
2.5.2 Number of Lags

To determine the appropriate number of lags, I run univariate models for each endogenous variable, with lags of the endogenous variable, the fixed effects, and the control variables. Then I determine the number of lags that produces the lowest AIC and BIC values. The exact model specification is:

\[ y_{fmt} = \alpha_1 + \alpha_{2f} + \alpha_{3y} + \alpha_{4q} + \sum_{i=1}^{k} \beta_{ki} y_{fmt(t-k)} \]

\[ + \gamma_1 HubO_{fmt} + \gamma_2 HubD_{fmt} + \gamma_3 Distance_m + \gamma_4 PopGeoMean_{mt}, \]

where \( \alpha_1 \) is the intercept, \( \alpha_{2f} \) is the firm-fixed effect, \( \alpha_{3y} \) is the year-fixed effect; \( \alpha_{4q} \) is the quarter-fixed effect; \( HubO_{fmt} \) is an indicator of whether the focal airline has a hub in the origin airport; \( HubD_{fmt} \) is an indicator of whether the focal airline has a hub in the destination airport; \( Distance_m \) is the distance between the origin airport and the destination airport; and \( PopGeoMean_{mt} \) is the geometric mean of the populations in the origin city and the destination city at time \( t \).

2.5.3 Missing Data

To impute missing price values, I create a matrix with information on price (observed and missing) and information on all other variables. First, I include price information that comprises three variables, namely, the first lag of price (if unavailable, I use the most recent lag value), the average price of the focal carrier across all markets, and the first lag of price for the focal carrier across all markets. Second, the matrix features four competition variables: the change in the average price of competitors in the current period; the average price per mile (i.e., average yield) for the route, calculated as the average price over all airlines that had price values available flying that route, which I divided by the distance in miles for that route; the number of competitors on the route; and number of low cost competitors on the route. Third, as airline variables, I used the number of passengers served, number of flights from the origin, market share, average delay in minutes, percentage of cancellations, number of airports the focal airline serves in the same MSA, percentage of departures performed in
the market, and age of the focal airline. Fourth, I included two market-specific two variables, distance in miles and the geometric mean of the populations in the origin and destination cities. Fifth, the time variables were gross domestic product and jet fuel market price.

I estimate the missing values using an iterative, two-step procedure (Darmawan, 2002; Little and Rubin, 1987; Schafer, 1997). In step 1, I impute the missing values by random draws from a conditional multivariate normal distribution (60 simulated iterations with an uninformative prior; Schafer (1997)), given the observed data and current covariance matrix of all the variables. In step 2, I update the covariance matrix with a Bayesian posterior distribution, given the observed data and most recent imputed missing values. I repeatedly iterate between these two steps until I achieve convergence.

2.5.4 Unobserved Heterogeneity

I use firm-, market-, and time-specific fixed effects, as well as fixed effects for each firm-market to account for unobserved heterogeneity (see Equations 2.1, 2.2, and 2.4). I cannot estimate these fixed effects, because they correlate with the error term, due to presence of lagged endogenous variables (e.g., Holtz-Eakin et al., 1987; Holtz-Eakin et al., 1988; Lundberg, 1985). Instead, I apply a first difference to Equation 2.4 to eliminate individual effects (Anderson and Hsiao, 1982; Arellano and Bond, 1991; Holtz-Eakin et al., 1988) and thus can
rewrite the equation as:

\[
\begin{bmatrix}
1 & 0 & 0 & -\beta_{14}^0 \\
0 & 1 & 0 & 0 \\
0 & -\beta_{32}^0 & 1 & 0 \\
0 & 0 & -\beta_{43}^0 & 1
\end{bmatrix}
\begin{bmatrix}
\Delta SQ_{f_{abt}} \\
\Delta P_{f_{abt}} \\
\Delta PS_{f_{abt}} \\
\Delta CapU_{f_{abt}}
\end{bmatrix}
= 
\begin{bmatrix}
\eta_{sq} & 0 & 0 & 0 \\
0 & \eta_p & 0 & 0 \\
0 & 0 & \eta_{ps} & 0 \\
0 & 0 & 0 & \eta_u
\end{bmatrix}
\begin{bmatrix}
\Delta SQ_{f_{bat}} \\
\Delta P_{f_{bat}} \\
\Delta PS_{f_{bat}} \\
\Delta CapU_{f_{bat}}
\end{bmatrix}
\]

\[
\begin{align*}
&\beta_{0_{sq}} + \sum_{c=1}^{C} \delta_{c_{sq}}^0 \Delta Comp_{c_{f_{abt}}} + \sum_{con=1}^{CON} \gamma_{con}^\alpha \Delta Control_{con,f_{abt}} \\
&\beta_{0_{pt}} + \sum_{c=1}^{C} \delta_{c_{p}}^0 \Delta Comp_{c_{f_{abt}}} + \sum_{con=1}^{CON} \gamma_{con}^\alpha \Delta Control_{con,f_{abt}} \\
&\beta_{0_{ps}} + \sum_{c=1}^{C} \delta_{c_{ps}}^0 \Delta Comp_{c_{f_{abt}}} + \sum_{con=1}^{CON} \gamma_{con}^\alpha \Delta Control_{con,f_{abt}} \\
&\beta_{bat} + \sum_{c=1}^{C} \delta_{c_{bat}}^0 \Delta Comp_{c_{f_{abt}}} + \sum_{con=1}^{CON} \gamma_{con}^\alpha \Delta Control_{con,f_{abt}} \\
&\sum_{\kappa=1}^{K} \left[ \begin{array}{cccc}
\beta_{11}^\kappa & \beta_{12}^\kappa & \beta_{13}^\kappa & \beta_{14}^\kappa \\
\beta_{21}^\kappa & \beta_{22}^\kappa & \beta_{23}^\kappa & \beta_{24}^\kappa \\
\beta_{31}^\kappa & \beta_{32}^\kappa & \beta_{33}^\kappa & \beta_{34}^\kappa \\
\beta_{41}^\kappa & \beta_{42}^\kappa & \beta_{43}^\kappa & \beta_{44}^\kappa
\end{array} \right] \times \\
\begin{bmatrix}
\Delta SQ_{f_{abt}^-\kappa} \\
\Delta P_{f_{abt}^-\kappa} \\
\Delta PS_{f_{abt}^-\kappa} \\
\Delta CapU_{f_{abt}^-\kappa}
\end{bmatrix}
\end{align*}
\]

The only fixed effects left after first differencing the equations are the time-specific effects, denoted $\beta_{0_{it}} = \alpha_{1_{it}} - \alpha_{1_{it}^-1}$. In Equation 2.12, the lagged dependent variables are endogenous, because they correlate with the error terms (Anderson and Hsiao, 1982; Arellano and Bond, 1991). For each $\Delta y_{it-k}$, $y_{it-k-1}$ serves as an instrumental variable, because it correlates with $\Delta y_{it-k}$ but is orthogonal to the error term (Anderson and Hsiao, 1982). To estimate Equation 2.12, I use the general method of moments, which is based on the orthogonality condition of instruments (i.e., $y_{it-k-1}, \Delta X_{it}^k$) and $\nu_{it}$ (Anderson and Hsiao, 1982; Holtz-Eakin et al., 1988).

### 2.5.5 Cross-Sectional Dependence

To account for the interdependence of each endogenous variable between each pair of markets, I estimate the level of cross-sectional dependence, denoted $\hat{\rho}$, then treat $\hat{\rho}$ as data when I implement the three-step PVAR estimation, as I detail in Section 2.4.6. (Mutl, 2009).
2.5.5.1 Stage 1: Instrumental variable regression to each equation in the VAR system

For each $Y$ variable ($Y$ stands for logit of delay, log of price, logit of capacity utilization, and log of number of passenger served), I have equations:

$$\Delta Y_{f_{abt}} = \beta_0 + \beta_1 \Delta Y_{f_{abt-1}} + \rho \Delta Y_{fbat} + \beta_2 \Delta X_{f_{abt}} + \nu_{f_{abt}}$$

$$\Delta Y_{fbat} = \beta_0 + \beta_1 \Delta Y_{f_{bat-1}} + \rho \Delta Y_{f_{abt}} + \beta_2 \Delta X_{f_{bat}} + \nu_{f_{bat}}$$

(2.13)

where $a, b$ stands for origin and destination airport, respectively (and together represent a market). For example, if $ab$ indicates JFK–LAX, $ba$ means the reciprocal LAX–JFK market.

In matrix form, I can rewrite Equation 2.13 as:

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta Y_{f_{abt}} \\ \Delta Y_{f_{bat}} \end{bmatrix} = \begin{bmatrix} \beta_0 \\ \beta_0 \end{bmatrix} + \begin{bmatrix} \beta_1 & 0 \\ 0 & \beta_1 \end{bmatrix} \begin{bmatrix} \Delta Y_{f_{abt-1}} \\ \Delta Y_{f_{bat-1}} \end{bmatrix} + \begin{bmatrix} 0 & \rho \\ \rho & 0 \end{bmatrix} \begin{bmatrix} \Delta Y_{f_{abt}} \\ \Delta Y_{f_{bat}} \end{bmatrix}$$

$$+ \begin{bmatrix} \beta_2 & 0 \\ 0 & \beta_2 \end{bmatrix} \begin{bmatrix} \Delta X_{f_{abt}} \\ \Delta X_{f_{bat}} \end{bmatrix} + \begin{bmatrix} \nu_{f_{abt}} \\ \nu_{f_{bat}} \end{bmatrix},$$

(2.14)

which is equivalent to

$$\begin{bmatrix} 1 & -\rho \\ -\rho & 1 \end{bmatrix} \begin{bmatrix} \Delta Y_{f_{abt}} \\ \Delta Y_{f_{bat}} \end{bmatrix} = \begin{bmatrix} \beta_0 \\ \beta_0 \end{bmatrix} + \begin{bmatrix} \beta_1 & 0 \\ 0 & \beta_1 \end{bmatrix} \begin{bmatrix} \Delta Y_{f_{abt-1}} \\ \Delta Y_{f_{bat-1}} \end{bmatrix} +$$

$$+ \begin{bmatrix} \beta_2 & 0 \\ 0 & \beta_2 \end{bmatrix} \begin{bmatrix} \Delta X_{f_{abt}} \\ \Delta X_{f_{bat}} \end{bmatrix} + \begin{bmatrix} \nu_{f_{abt}} \\ \nu_{f_{bat}} \end{bmatrix}.$$

(2.15)

Then, I let $C = \begin{bmatrix} 1 & -\rho \\ -\rho & 1 \end{bmatrix}$, $\Delta Y_t = \begin{bmatrix} \Delta Y_{f_{abt}} \\ \Delta Y_{f_{bat}} \end{bmatrix}$, $\Delta Y_{t-1} = \begin{bmatrix} \Delta Y_{f_{abt-1}} \\ \Delta Y_{f_{bat-1}} \end{bmatrix}$, $\Delta X_t = \begin{bmatrix} \Delta X_{f_{abt}} \\ \Delta X_{f_{bat}} \end{bmatrix}$, and $\nu_t = \begin{bmatrix} \nu_{f_{abt}} \\ \nu_{f_{bat}} \end{bmatrix}$, in which case I can rewrite Equation 2.15 as:

$$C \Delta Y_t = \beta_0 + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta X_t + \nu_t.$$  

(2.16)
If I multiply Equation 2.16 by $C^{-1}$, I obtain:

$$
\Delta Y_t = C^{-1} \beta_{0t} + C^{-1} \beta_1 \Delta Y_{t-1} + C^{-1} \beta_2 \Delta X_t + C^{-1} \nu_t. \quad (2.17)
$$

Finally, using $Y_{t-2}$ to instrument $\Delta Y_{t-1}$, and applying an IV regression to Equation 2.16, I derive the fitted value $\widehat{C^{-1}} \nu_t$ of the residual in Equation 2.17.

### 2.5.5.2 Stage 2: Estimate $\hat{\rho}$

After collecting $\widehat{C^{-1}} \nu_t$ from stage 1, I can estimate $\widehat{C^{-1}}$ on the basis of $\text{Cov}(\widehat{C^{-1}} \nu_t)$, where $\nu_t$ is assumed to be distributed i.i.d $N(0, \sigma^2)$: $\text{Cov}(\widehat{C^{-1}} \nu_t) = E(\widehat{C^{-1}} \nu_t \nu_t') = \widehat{C^{-1}} E(\nu_t \nu_t') \widehat{C^{-1}}' = \widehat{C^{-1}} \sigma^2 \widehat{C^{-1}}'$. I also can estimate $\hat{\rho}$ on the basis of $\widehat{C^{-1}}$.

### 2.5.5.3 Stage 3: Estimate the PVARX model with $\hat{\rho}$

If I insert $\hat{\rho}$ into Equation 2.14, I obtain:

$$
\begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix}
\begin{bmatrix}
\Delta Y_{f_{bat}} \\
\Delta Y_{f_{bat}}
\end{bmatrix} =
\begin{bmatrix}
\beta_{0t} \\
\beta_{0t}
\end{bmatrix} +
\begin{bmatrix}
\beta_1 & 0 \\
0 & \beta_1
\end{bmatrix}
\begin{bmatrix}
\Delta Y_{f_{bat-1}} \\
\Delta Y_{f_{bat-1}}
\end{bmatrix} +
\begin{bmatrix}
0 & \hat{\rho} \\
0 & 0
\end{bmatrix}
\begin{bmatrix}
\Delta Y_{f_{bat}} \\
\Delta Y_{f_{bat}}
\end{bmatrix}
+\begin{bmatrix}
\beta_2 & 0 \\
0 & \beta_2
\end{bmatrix}
\begin{bmatrix}
\Delta X_{f_{bat}} \\
\Delta X_{f_{bat}}
\end{bmatrix} +
\begin{bmatrix}
\nu_{f_{bat}} \\
\nu_{f_{bat}}
\end{bmatrix},
$$

(2.18)

I treat $\hat{\rho}$ as data to compute a new set of dependent variables, and I estimate the model using the PVARX estimation procedures described in Section 2.4.6. (Huang, 2008; Muli, 2009):

$$
\begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix}
\begin{bmatrix}
\Delta Y_{f_{bat}} \\
\Delta Y_{f_{bat}}
\end{bmatrix} -
\begin{bmatrix}
0 & \hat{\rho} \\
\hat{\rho} & 0
\end{bmatrix}
\begin{bmatrix}
\Delta Y_{f_{bat}} \\
\Delta Y_{f_{bat}}
\end{bmatrix} =
\begin{bmatrix}
\beta_{0t} \\
\beta_{0t}
\end{bmatrix} +
\begin{bmatrix}
\beta_1 & 0 \\
0 & \beta_1
\end{bmatrix}
\begin{bmatrix}
\Delta Y_{f_{bat-1}} \\
\Delta Y_{f_{bat-1}}
\end{bmatrix} +
\begin{bmatrix}
\beta_2 & 0 \\
0 & \beta_2
\end{bmatrix}
\begin{bmatrix}
\Delta X_{f_{bat}} \\
\Delta X_{f_{bat}}
\end{bmatrix} +
\begin{bmatrix}
\nu_{f_{bat}} \\
\nu_{f_{bat}}
\end{bmatrix},
$$

(2.19)
2.5.6 PVAR Estimation

Now that I have first differenced the VARX system to remove various fixed effects, corrected for cross-sectional dependence, and multiplied both sides of the VARX system by $C^{-1}$ (the inverse of the matrix capturing contemporaneous effects among endogenous variables), I can apply the three-stem procedure proposed by Holtz-Eakin et al. (1987) to estimate the PVARX model.

First, I use two-stage least square estimates of on each endogenous variable for each time period (i.e., estimate Equation 2.12 for each time period, and treat $\beta_{0,t}$ as the intercept), using the following two-stage least square estimator:

$$\hat{B}_t = [W'_tZ_t(Z'_tZ_t)^{-1}Z'_tW_t]^{-1}W'_tZ_t(Z'_tZ_t)^{-1}Z'_tY_t,$$

where $W_t$ is the regressor vector, and $Z_t$ is the instrument vector (i.e., $y_{it-k-1}, \Delta X_{it}$). Then I can calculate a vector of residuals for period $t$: $\hat{\nu}_t = Y_t - W_t\hat{B}_t$.

Second, to construct the weighting matrix $E(Z'VV'Z)$, I use:

$$\hat{\Omega} = \frac{\sum_{i=1}^{N}(\nu_{ir}\nu_{is}Z'_{ir}Z_{is})}{N}$$

where $\nu_{it}, t = r, s$ is the $ith$ element (observation) of $V_t$, $Z_{it}$ is the $ith$ row of $Z_t$, and $N$ is the number of observations in each time period.

Third, to obtain a generalized least squares estimator of the entire parameter vector, I stack all four endogenous variables and use all available observations, as specified in Equation 2.12. Because I have 72 time periods, I define $\beta_t = \beta_q + \lambda^X \Delta X_t + \lambda^D D_t$, where $q = 4$ for change in quarter $1 \rightarrow 2, 2 \rightarrow 3, 3 \rightarrow 4, or 4 \rightarrow 1, and D_t = 1, if q = 2 \rightarrow 3, 3 \rightarrow 4 in year 2001 and q = 4 \rightarrow 1, 1 \rightarrow 2 in year 2002. Thus,

$$\hat{B}_t = [W'Z\hat{\Omega}^{-1}Z'W]^{-1}W'Z\hat{\Omega}^{-1}Z'Y,$$

This three-step estimation procedure (Holtz-Eakin et al., 1987) applies to balanced panel data, so I must adapt it to the unbalanced panel setting, in which the number of firms varies
across markets, and the time dimension varies across firm–market configurations. I adapt the second step and construct a weighting matrix for the unbalanced panel structure, rewriting Equation 2.21 as:

$$\hat{\Omega} = \sum_{i=1}^{N} (\nu_{it} \nu_{is} Z'_{it} Z_{is}) / \min(N_r, N_s),$$  \hspace{1cm} (2.23)

where $\nu_{it}, t = r, s$ is the ith element (observation) of $V_t$, $Z_{it}$ is the ith row of $Z_t$, and $N_t, t = r, s$ is the number of observations in time period $t$. The number of observations in time $r$ might differ from that in time $s$, but I only need observations that appear in both periods to estimate the weighting matrix $\Omega$, which captures the average interperiod connections. Therefore, I use the minimum number of observations in time $r$ and time $s$ to construct $\hat{\Omega}$, because information on cross-period dependence can be gleaned only from observations that exist over consecutive time periods.

2.6. Results

2.6.1 Missing Data

I use the mean value from 60 imputations to find missing price data values, assuming a MAR mechanism. To assess the accuracy of my imputation method, I performed an experiment with data from 1993 to 2002, for which there are no missing values. For this data set, I created a holdout sample by deleting price data in a pattern similar to the missing value pattern (i.e., same airline, same market, similar proportion of missing values) in the overall data set (1993–2010). After imputing the missing values in the holdout sample, I calculated the mean square error: $\frac{\sum_{m=1}^{M} (\hat{p}_m - p)^2}{M}$, (where $\hat{p}$ is the estimated price, $p$ is the true price, and $M$ is the number of observations with missing price values). I thus assess the accuracy of my imputation method; the resulting mean square error of 5.7% seemed reasonable.

2.6.2 Unit Root Tests

The Choi tests (Equations 2.9 and 2.10) showed that the $p$ value corresponding to the $Z$ value was statistically significant for transformed data for service quality, price, and capacity
utilization ($p < .01$); that is, the data-generating processes for these three variables appear stationary. For number of passengers served, the $p$-value corresponding to $Z$ is marginally statistically significant ($< .06$), which suggests the possibility of a unit root; however, the first difference for the number of passengers served data series is stationary ($p < .01$). As I elaborate in the PVAR estimation, I first difference the data to eliminate the individual effects (Anderson and Hsiao, 1982; Holtz-Eakin et al., 1988), which makes the data series for number of passengers served stationary. Thus, I am not concerned about any unit root issues among the four endogenous variables.

### 2.6.3 Number of Lags

The lowest AIC and BIC values, from the estimation of Equation 10, result when I use one lag for each of the four endogenous variables. I use this one-lag value in all the models.

### 2.6.4 Cross-Sectional Dependence

I find evidence of cross-sectional dependence (Equation 18), in that the estimates of $\rho$ are positive for the four endogenous variables (see Table 2.4). These results confirm the idea that most passengers buy round-trip tickets. Thus, the service quality, price, and performance metrics are positively related for reciprocal routes.

### 2.6.5 Panel VAR

I present the results of my PVAR estimation in Table 2.5. I estimate the contemporaneous effects (Equation 2.2) from the variance-covariance matrix of the residuals. The results

---

Table 2.4: Cross-Sectional Dependence

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Cross-Sectional Dependence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service Quality (logit(delay))</td>
<td>.153** (.01)</td>
</tr>
<tr>
<td>log(Price)</td>
<td>.245* (.07)</td>
</tr>
<tr>
<td>logit(CapUtilization)</td>
<td>.260** (.05)</td>
</tr>
<tr>
<td>log(Number of Passenger Served)</td>
<td>.250** (.04)</td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses.

* $p < 0.01$ ** $p < 0.001$. 
suggest that as price increases, the number of passengers served decreases ($\beta_{32} = -0.873, p < .01$) consistent with a standard notion of a downward sloping demand curve. As the number of passengers served increases, capacity utilization decreases ($\beta_{43} = -0.758, p < .01$); to meet increasing demand, airlines apparently add capacity, which then reduces capacity utilization. Finally, as capacity utilization increases, service quality decreases ($\beta_{14} = 0.0847, p < .05$), which reinforces the basic idea that service quality declines with fuller flights (Ramdas and Williams, 2008).

I present the estimated coefficients for the lagged endogenous variables and the exogenous variables in Table 2.6. The coefficients of the endogenous variables cannot be interpreted directly, because of the feedback mechanism among the endogenous variables, so I use impulse response functions (IRFs) to glean insights (Hamilton, 1994). Specifically, for my PVAR system, I use coefficient bootstrapping to compute the IRF (Love and Zicchino, 2006). To calculate these IRFs, I consider a one standard deviation (1) decrease in price, (2) increase in service quality (i.e., decrease in delay), (3) increase in capacity utilization, and (4) increase in number of passengers served. In the IRF plots in Figures 2.3 and 2.4, I note the change in one endogenous variable, in response to a one standard deviation shift in another endogenous variable, over eight periods. The $Y$ axes represent the value of the endogenous variable, and the $X$ axes indicate time (the shock occurs at $t_0$, and the focal endogenous variable starts to change at $t_1$). As is common practice, the red concrete line indicates the difference in the value of the endogenous variable for the shift compared to the condition when there is no shift (thus the x-axes can be seen as representing this no shift condition); the two dashed lines represent the 95% confidence interval bands of the red-concrete line.

### 2.6.5.1 Impact on Service Quality

Greater service quality, which means a decrease in delays (Figure 2.3, Panel A), improves service quality in the next period, and this improvement persists for around five periods, in support of persistence in service quality. In contrast, Panel B of Figure 2.3 shows that lower prices lead to lower service quality, which remains for four periods. Greater capacity utilization seems to improve service quality for around four periods (Panel C, Figure 2.3), but a change in the number of passengers served does not influence service quality (Panel
Table 2.5: Panel VAR Results

<table>
<thead>
<tr>
<th>Variable Category</th>
<th>Variable Name</th>
<th>Service Quality (logit (Delay))</th>
<th>Price</th>
<th>Number of Passengers Served</th>
<th>Capacity Utilization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feedback</td>
<td>Lag logit(delay)</td>
<td>3.11E-01***</td>
<td>-4.14E-03</td>
<td>4.75E-03</td>
<td>-1.28E-02*</td>
</tr>
<tr>
<td></td>
<td>(1.30E-02)</td>
<td>(1.02E-02)</td>
<td>(5.80E-03)</td>
<td>(7.70E-03)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lag log(price)</td>
<td>-1.66E-01**</td>
<td>-4.06E-01***</td>
<td>-1.65E-01***</td>
<td>-3.92E-02**</td>
</tr>
<tr>
<td></td>
<td>(2.75E-02)</td>
<td>(2.50E-02)</td>
<td>(1.47E-02)</td>
<td>(1.82E-02)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lag logit(capacity utilization)</td>
<td>-6.62E-02*</td>
<td>-1.75E-01***</td>
<td>-1.24E-01***</td>
<td>4.10E-01***</td>
</tr>
<tr>
<td></td>
<td>(3.45E-02)</td>
<td>(3.32E-02)</td>
<td>(1.80E-02)</td>
<td>(2.22E-02)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lag log(number of passengers served)</td>
<td>-2.76E-02</td>
<td>-1.10E-01</td>
<td>8.73E-02*</td>
<td>-6.72E-02**</td>
</tr>
<tr>
<td></td>
<td>(9.12E-02)</td>
<td>(7.96E-02)</td>
<td>(4.82E-02)</td>
<td>(4.92E-02)</td>
<td></td>
</tr>
<tr>
<td>Potential competition</td>
<td>Total number of competitors</td>
<td>7.35E-03**</td>
<td>-5.74E-03**</td>
<td>3.35E-04</td>
<td>1.23E-02**</td>
</tr>
<tr>
<td></td>
<td>(3.12E-03)</td>
<td>(2.57E-03)</td>
<td>(1.18E-03)</td>
<td>(2.10E-03)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total number of low cost competitors</td>
<td>-1.02E-02</td>
<td>6.85E-03</td>
<td>7.46E-03*</td>
<td>1.01E-02</td>
</tr>
<tr>
<td></td>
<td>(1.07E-02)</td>
<td>(8.03E-03)</td>
<td>(3.91E-03)</td>
<td>(6.77E-03)</td>
<td></td>
</tr>
<tr>
<td>Realized competition</td>
<td>Competitors' mean price</td>
<td>2.34E-05</td>
<td>8.24E-05***</td>
<td>-4.61E-05***</td>
<td>-5.20E-05*</td>
</tr>
<tr>
<td></td>
<td>(3.83E-05)</td>
<td>(2.33E-05)</td>
<td>(1.42E-05)</td>
<td>(2.36E-05)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Competitors' mean delay</td>
<td>-2.09E+00***</td>
<td>-1.46E-02</td>
<td>2.86E-02*</td>
<td>1.45E-01***</td>
</tr>
<tr>
<td></td>
<td>(3.12E-02)</td>
<td>(2.84E-02)</td>
<td>(1.45E-02)</td>
<td>(2.45E-02)</td>
<td></td>
</tr>
<tr>
<td>Control Variables</td>
<td>Multiple airport occupation</td>
<td>3.05E-02</td>
<td>-3.57E-02*</td>
<td>-2.06E-02</td>
<td>6.40E-02***</td>
</tr>
<tr>
<td></td>
<td>Network size</td>
<td>-2.28E-05***</td>
<td>-7.34E-06*</td>
<td>2.85E-05***</td>
<td>-3.02E-05**</td>
</tr>
<tr>
<td></td>
<td>(5.59E-06)</td>
<td>(3.77E-06)</td>
<td>(1.95E-06)</td>
<td>(3.15E-06)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Airport congestion</td>
<td>6.40E-06**</td>
<td>-2.09E-06</td>
<td>1.12E-05***</td>
<td>3.45E-05***</td>
</tr>
<tr>
<td></td>
<td>(2.66E-06)</td>
<td>(1.75E-06)</td>
<td>(9.01E-07)</td>
<td>(1.52E-06)</td>
<td></td>
</tr>
<tr>
<td>Time effects</td>
<td>Jet fuel cost</td>
<td>6.87E-03*</td>
<td>1.60E-02***</td>
<td>8.97E-04</td>
<td>-8.78E-05</td>
</tr>
<tr>
<td></td>
<td>Unemployment rate</td>
<td>5.61E-02***</td>
<td>2.36E-03</td>
<td>5.40E-03</td>
<td>-1.07E-02*</td>
</tr>
<tr>
<td></td>
<td>(8.11E-03)</td>
<td>(7.85E-03)</td>
<td>(3.80E-03)</td>
<td>(6.32E-03)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Q1→Q2</td>
<td>-8.8E-02***</td>
<td>3.84E-03</td>
<td>8.07E-02***</td>
<td>2.42E-01**</td>
</tr>
<tr>
<td></td>
<td>(9.33E-03)</td>
<td>(6.18E-03)</td>
<td>(4.06E-03)</td>
<td>(5.67E-03)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Q2→Q3</td>
<td>2.32E-02**</td>
<td>2.41E-02**</td>
<td>2.62E-02**</td>
<td>-1.40E-01**</td>
</tr>
<tr>
<td></td>
<td>(1.10E-03)</td>
<td>(1.15E-02)</td>
<td>(5.79E-03)</td>
<td>(7.83E-03)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Q3→Q4</td>
<td>1.30E-02**</td>
<td>-9.83E-03**</td>
<td>-5.11E-02**</td>
<td>-1.44E-01**</td>
</tr>
<tr>
<td></td>
<td>(5.83E-03)</td>
<td>(4.78E-03)</td>
<td>(2.75E-03)</td>
<td>(4.10E-03)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Q4→Q1</td>
<td>7.71E-02**</td>
<td>6.75E-03</td>
<td>-5.31E-02**</td>
<td>5.38E-02**</td>
</tr>
<tr>
<td></td>
<td>(8.04E-03)</td>
<td>(7.03E-03)</td>
<td>(3.76E-03)</td>
<td>(6.07E-03)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>9.11 Effect</td>
<td>-1.68E-02</td>
<td>-3.72E-02***</td>
<td>-1.11E-02*</td>
<td>3.76E-03</td>
</tr>
<tr>
<td></td>
<td>(3.50E-02)</td>
<td>(5.13E-03)</td>
<td>(6.41E-03)</td>
<td>(1.20E-02)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: I report standard error in parentheses. The dependent variable used to measure service quality is the logit transformation of percentage delay; the coefficients in that column should be interpreted as the positive/negative effects on percentage delay increase/decrease, that is, the negative/positive effects on service quality.

* p < 0.10. ** p < 0.05. *** p < 0.01.
Table 2.6: Summary of Effects of Endogenous Variables

<table>
<thead>
<tr>
<th>Endogenous variable at time $t-1$</th>
<th>Price at time $t$</th>
<th>Service Quality at time $t$</th>
<th>Capacity utilization at time $t$</th>
<th>Passenger flow at time $t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service Quality ↑</td>
<td>–</td>
<td>↑</td>
<td>↑</td>
<td>–</td>
</tr>
<tr>
<td>Price ↓</td>
<td>↑</td>
<td>↓</td>
<td>↑</td>
<td>↑</td>
</tr>
<tr>
<td>Capacity utilization ↑</td>
<td>↓</td>
<td>↑</td>
<td>↑</td>
<td>↑</td>
</tr>
<tr>
<td>Number of passengers served ↑</td>
<td>–</td>
<td>–</td>
<td>↓</td>
<td>↑</td>
</tr>
</tbody>
</table>

D, Figure 2.3).

![Panel A: Shock to Service Quality](image1)

![Panel B: Shock to Price](image2)

![Panel C: Shock to Capacity Utilization](image3)

![Panel D: Shock to Number of Passenger Served](image4)

Figure 2.3: Impact on Service Quality: Impulse Response Functions
Figure 2.4: Impact on Price: Impulse Response Functions

2.6.5.2 Impact on Price

Panel A in Figure 2.4 shows that a shock to service quality does not influence price; I elaborate on this surprising finding subsequently. In contrast, a decrease in price results in an increase in price in the next period, though this increase dissipates rather quickly (Panel B, Figure 2.4). It appears that firms thus alternate between increases and decreases. An increase in capacity utilization results in a decrease in price, which remains in place for about four periods (Panel C, Figure 2.4). An increase in the number of passengers has little influence on price though (Panel D, Figure 2.4). Airlines thus appear to respond to capacity utilization, but not demand management (i.e., passengers served), issues with price changes.\footnote{\textsuperscript{8}}

\footnote{\textsuperscript{8}}I also examined the impulse response functions for the effect on capacity utilization and number of passengers served (for plots see supplementary document). For capacity utilization, when airlines improve their service quality, it increases capacity utilization slightly, for around four periods; customers respond positively to improvements in service quality. Decreases in price also slightly increase capacity utilization, consistent with a downward sloping demand curve, which persists for around four periods. More capacity
2.6.5.3 Competitive Effects

Because the competition variables are exogenous, I use the coefficients reported in Table 2.6 to assess their influence. Price seems influenced by both potential and realized competition: The number of competitors drives the price down \((b = -5.74E - 03; p < .05)\), and as competitors’ prices increase, the focal airline’s price does as well \((b = 8.24E - 05; p < .01)\). Thus, competition is critical for determining price.

The results for service quality and competition are somewhat more complex. With greater potential competition, service quality declines \((b = 7.35E - 03; p < .05)\); however, the service quality levels of competitors positively influences the focal airline’s service quality \((b = 2.09E + 00; p < .01)\). It is important to note that my results related to service quality and potential competition contradict those reported by Mazzeo (2003) and Rupp et al. (2006); to resolve this inconsistency, I replicate the cross-sectional analyses that the two previous studies report using the data.\(^9\) In Table 2.7, I provide the ordinary least squares results for a service quality model that accounts for airline and time-fixed effects. To control for market-level effects, I include covariates for distance and the populations of origin and destination cities. For one potential competition variable (total number of low cost carriers has a significant negative effect), I find a result consistent with prior findings \((b = -3.5E - 02; p < .01)\) (Mazzeo, 2003; Rupp et al., 2006). However, the prior studies do not estimate price and service quality jointly with feedback between them and only account for potential completion (i.e., not realized competition). Thus, my results provide deeper and more statistically sound insights.

\(^9\) Whereas Mazzeo (2003) and Rupp et al. (2006) collect flight-level data and model it as cross-sectional (i.e., data come from flights of a particular airline in a particular market at a point in time), I use firm-market-time-level data.
Table 2.7: Results of Mazzeo Replication

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-2.059***</td>
</tr>
<tr>
<td>Competitors’ mean delay</td>
<td>1.84***</td>
</tr>
<tr>
<td>Total number of competitors</td>
<td>-0.002</td>
</tr>
<tr>
<td>Total number of low cost competitors</td>
<td>-0.035***</td>
</tr>
<tr>
<td>Airport congestion</td>
<td>4.027E-7**</td>
</tr>
<tr>
<td>Out of hub</td>
<td>0.277***</td>
</tr>
<tr>
<td>Into hub</td>
<td>-0.013*</td>
</tr>
<tr>
<td>Distance</td>
<td>-3.27E-5***</td>
</tr>
<tr>
<td>Origin city population</td>
<td>1.07E-8***</td>
</tr>
<tr>
<td>Destination city population</td>
<td>1.49E-8***</td>
</tr>
</tbody>
</table>

Notes: Dependent variable = logitDelay; Adjusted $R^2 = 0.314$.
*p < 0.10. ** p < 0.05. *** p < 0.01.

2.6.5.4 Control Variables

The control variables also influence the four endogenous variables. More airport congestion (number of flights departing from the origin airport) decreases the prices. Price is also lower for airlines that operate from two airports in a MSA, rather than just one.

Service quality increases with market power, as indicated by network size. That is, when the number of flights by airline departing from an origin airport increases, which implies greater dominance by that airline, the resources at its disposal also increase (Ciliberto and Williams, 2011), which improves its service quality. Consistent with extant research (e.g., Mazzeo, 2003; Rupp et al., 2006), I find that service quality decreases with more airport congestion though.

Capacity utilization increases with a smaller network size and greater airport congestion, as well as when the airline serves multiple airports from a MSA. Finally, the number of passengers served increases with market power, as indicated by network size, and with airport congestion.
2.7. Conclusion

Service quality and price decisions are critical for service firms; I have sought to model the interplay across these strategic marketing decisions and performance outcomes in the presence of both realized and potential competition. I gather a unique, multisource data set pertaining to the airline industry and develop a structural panel VAR model that captures its idiosyncrasies, such as cross-sectional dependencies and missing observations.

My findings suggest interesting patterns of asymmetry effects among the endogenous variables. In particular, I note the asymmetry between service quality and price; though service quality decisions adjust to price, my results suggest that pricing decisions are not adjusted to service quality. Together with the result for competition variables, this finding indicates that firms adjust their prices primarily to manage capacity and in response to potential and realized competition. Service quality decisions instead reflect considerations of price, performance, and competitive factors. Finally, price exerts more of an impact on the two performance measures than does service quality; it influences both capacity utilization and demand, whereas service quality only affects capacity utilization.

Beyond these unique findings and the substantive insights they provide into service quality and pricing decisions in the airline industry, I introduce several unique elements in the model. To build the model, I explicitly recognized key features of the data, which supported the three-way structural PVAR, with exogenous competition and control variables. With this model, I could glean contemporaneous and lagged effects and understand the complexities inherent in service quality and pricing decisions at the market level for industries in which firms compete in multiple markets. A clear insight arises with regard to potential competition for service quality; in contrast with extant cross-sectional studies (Mazzeo, 2003; Rupp et al., 2006), I find that greater potential competition (number of competitors) leads to diminished service quality. If I combine this outcome with the result related to realized competition, I can posit that more competitors deteriorates service quality because it demands more sharing of resources in the market (e.g., airport facilities), whereas realized competition positively influences service quality, as should be expected in a competitive setting. The panel nature of my model allows for the many cross-sections in the data in terms of firms and
markets; the VAR component acknowledges the system of multiple equations that influence one another. I also recognize several other complexities in the data, including cross-sectional dependencies and missing values. My model thus can capture the complexities inherent in modeling marketing mix variables for dynamic competition among firms across multiple markets.

Despite these model and estimation complexities, my primary objective has been to provide insights into the interplay of service quality and price—two primary marketing decision variables for service firms—in the presence of competition. My results provide some key insights, especially for the airline industry. The extent to which these findings generalize to other service industries, such as hotels and banking, should be the topic of further empirical investigations. I also provide groundwork for additional theoretical models; for example, new theoretical models might depict the asymmetry between service quality and price, such that service quality is influenced by price but price is not influenced by service quality, to support decisions about both variables.
Chapter 3

Modeling Service Quality: The Impact of Firm, Demand, and Competitive Factors

Abstract

Service delivery comprises different dimensions based on industrial contextual factors, such as market characteristics, competitive responses, and firm characteristics that influence service quality decisions across these dimensions. In this chapter, I explore how firms’ service quality decisions are influenced by market and firm characteristics, and competitors’ service quality decisions. I apply the static game framework to account for the competitive interaction among firms. In the U.S. airline context, the context of my research, flight cancellations and delays are two critical service quality dimensions that firms strategically adjust by choosing relevant resource inputs, such as ground support, fleet scheduling, and crew assignment. I develop a static discrete game to model these two service quality decisions, using data provided by the U.S. Bureau of Transportation Statistics. In my model, firms rationally anticipate each other’s actions and I estimate firms’ service quality choices as a system of simultaneous discrete choice models. The results show that firms tend to provide high service quality on both dimensions under the following three conditions: (1) when there are many businesses in the market, which indicates a strong potential demand from business customers; (2) when firms have high capacity utilization, which suggests that more efficient capacity management also leads to better service quality; and (3) when competitors provide low service quality in one dimension either by having high flight cancellations or high delays, leading to incentives for firms to provide high service quality in both dimensions to differentiate themselves. The results also show that firm-specific factors and competitive responses have asymmetric impacts on flight cancellation and delay decisions; more specifically, flight cancellation decisions are largely driven by the amount of flight supply and the
level of capacity utilization, whereas firms respond to competition mainly by adjusting their average delays. Finally, my model allows me to test two counterfactual situations of hypothetical absences of new entrant firms, measure the expected response of the incumbent competitors, and quantify the impact of the presence of new entrant firm(s) of various service quality levels on incumbent competitors.
3.1. Introduction

In the airline industry, flight on-time performance is a basic but important indicator of service quality. To most consumers, it is important to safely arrive at the destination on the scheduled time. Indeed, Bureau of Transportation Statistics (BTS) publishes Air Travel Consumer Reports yearly to track on-time performances of major firms (airlines). Some media press and online search engines, such as New York Times and FindTheBest, track and compare the on-time performances of major firms from time to time, to provide references for consumers to choose which firm(s) to fly with. Though the on-time performance of a firm is influenced by uncontrollable factors, such as weather, airport congestion, etc., firms are able to control their on-time performances to a large extent. For instance, United Airlines started to offer on-time bonuses to employees since 2008, such that employees are willing to facilitate the process of transiting aircrafts from serving one flight to another. Southwest Airlines strategically constrained their aircrafts to a limited set of models to reduce the burden of aircrafts and crews scheduling/rescheduling. Many firms, such as KLM, Air France and Eagles Air, implemented specific programs for aircrafts maintenance and ground support staff training, to prepare aircrafts for the next scheduled flight efficiently.

It is important for firms to provide good on-time performance, and it seems feasible for them to improve it. We then may expect most firms to have good on-time records. However, this inference does not seem to be true. The Air Travel Consumer Reports show that from 2009 to 2010, Delta Airlines had 17.5% of flights delayed and JetBlue had 23.8% of flights delayed. It shows that some major firms do provide substantial amount of delayed flight services, despite the importance of on-time performance. As discussed above, firms are able to allocate resources to improve their on-time performance. The numbers reported in the Air Travel Consumer Reports suggest that some major firms choose not to allocate sufficient resources to flight on-time performance.

If we compare the on-time performances of firms in different markets, we may find that they differ substantially across firms and markets. For example, in the third quarter of 2010, American Airlines had 44% of flights delayed for more than 15 minutes in the Los Angeles-Denver market; in comparison, Southwest Airlines had a much better performance with
only 28% of flights delayed in that market (Figure 3.1). In the market St. Louis-Seattle, for the same quarter, the situation was reversed, with American Airlines having 26% of flights delayed and Southwest having 36% of flights delayed. The flip in relative on-time performance in these two markets seems to suggest that firms strategically allocate different levels of service-related resources in different markets.

Firms’ decisions on service related allocation frequently involve a trade-off between reducing costs and increasing quality dimensions (Anderson, Fornell and Rust, 1997; Rust, Moorman and Dickson, 2002). Managers must decide not only how to allocate resources to service quality versus other aspects of the business (e.g., improving productivity) but also how to allocate the service pool of resources across different markets. These decisions may be largely influenced by resource requirements to improve service quality, the impact of service quality on demand, and how competitors’ service quality is likely to change in response to the focal firm’s actions.

This paper aims at explaining firms’ decisions on service quality by disentangling three groups of driving factors, which I refer to as firm characteristics, market characteristics, and competitive factors, and quantifying the impact of each factor on the service quality decision. I use the airline industry of the United States as my research context. In the airline industry, the core service is the journey (i.e., transport passengers from city A to city B). Passengers usually expect to arrive at their destinations on time; however, it is not uncommon that flights are cancelled or delayed (Mazzeo, 2003; Rupp and Holmes, 2006). I thus use both flight cancellation rate and flight delay rate of a firm in a market, which I define as a route (e.g., Atlanta-Los Angeles), to represent the firm’s service quality level in the market. In addition, to account for the competitive interaction among firms, I propose a static discrete game (other examples of similar approaches included Bajari, Hong, Krainer and Nekipelov (2005) and Ellickson and Misra (2008)), in which service quality choice is defined as a unique combination of cancellation and delay level.

I use data from the airline industry in the United States to estimate the model. I find that firms tend to provide high service quality on both dimensions under the following three conditions: (1) when there are many businesses in the market, which indicates a strong
potential demand from business customers\(^1\); (2) when firms have high capacity utilization, which suggests that more efficient capacity management also leads to better service quality; and (3) when competitors provide low service quality on one dimension either by having high flight cancellations or high delays, leading to incentives for firms to provide high service quality on both dimensions to differentiate themselves. I also find that firm-specific factors and competitive responses have asymmetric impacts on flight cancellation and delay decisions; more specifically, flight cancellation decisions are largely driven by the amount of flight supply and the level of capacity utilization, whereas firms respond to competition mainly by adjusting their delays.

This research contributes to the services marketing literature, the airline industry related research, and the static discrete game literature. While most service marketing research focuses on the outcome of good services (e.g., Rust et al. 2000; Lariviere 2008), this research focuses on understanding the factors that influence service quality decisions, making use of objective service quality measures (e.g., on-time performance) instead of perceived service quality. Building on the airline industry related literature, I estimate how various simultaneous factors, including market characteristics, firm characteristics, and competition, drive manager decisions in the airline industry. This research also makes use of recent state-of-the-art developments in static discrete game literature to gain insights about how firms vertically differentiate their quality across various service dimensions in response to competitors’ service quality choices.

I organize the remainder of the chapter as follows. In Section 3.2, I provide a brief review

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\(^1\)Note that business customers travel both business class and economy class. I do not have data to distinguish the class of travel.
of the service marketing literature and the static discrete game literature. In Section 3.3, I provide the background information about how flight cancellations and delays happen. In Section 3.4, I describe my data set and relevant variables. After specifying the model in Section 3.5, I present the estimation details and identification strategy in Section 3.6. The main results, a discussion of their implications, and robustness checks appear in Section 3.7. I conduct counterfactual analyses to measure the impact of new entrants on incumbents service quality decisions in Section 3.8. Finally, in Section 3.9, I discuss the insights generated from these results and conclude the paper with managerial implications and directions for future research.

3.2. Literature Review

This research pertains to the service marketing literature, in which service quality is reflected by some measurable combination of tangibility, reliability, responsiveness, assurance, and empathy (Parasuraman, Berry and Zeithaml, 1985; Parasuraman et al., 1988; Parasuraman et al., 1991). Various studies establish positive outcomes of improved service quality, such as greater customer satisfaction and retention (e.g., Lariviere, 2008; Spreng and Mackoy, 1996; Zeithaml et al., 1996), increased market share (Rust et al., 2000), and higher shareholder value (Grewal et al., 2010). Other research distinguishes how customer satisfaction can be influenced by service quality at each stage of the service delivery process (e.g., Danaher and Mattsson, 1994; de Ruyter, Wetzels, Lemmink and Mattsson, 1997). A few studies also discuss how firms improve service quality by being market oriented (Raju and Lonial, 2001), formalizing the selling process, and/or applying a cross-functional team structure (Froehle et al., 2000). Previous applications generally measure service quality using consumer surveys (e.g., Lariviere, 2008; Raju and Lonial, 2001) that capture perceived instead of actual service quality. This research adds to this literature by focusing on understanding the factors that influence service quality decisions, making use of objective service quality measures (e.g., on-time performance) instead of perceived service quality.

This research is also related to past literature on the airline industry. In this area, previous work have established that perceived service quality enhances customer loyalty (Zins, 2001),
whereas poor service quality negatively moderates the positive effects of aircraft productivity on return on assets and sales (Sim, Koh and Shetty, 2006). Jou, Lam, Hensher, Chen and Kuo (2008) estimate a static demand-cost equilibrium, and shows that safety, convenience, and service quality (based on customer satisfaction surveys) increase demand. Some studies specifically explore the on-time performance of airlines and show that delay and cancellation performances are interdependent across airlines (Ball, Hoffman, Chen and Vossen, 2000) and that airlines have relatively lower delay and cancellation rates when competition is more severe compared with when competition is mild (Mazzeo, 2003; Rupp and Holmes, 2006; Rupp et al., 2006). Furthermore, studies in other industries assess how firms choose quality levels (e.g., motel vs. hotel; self-service vs. full-service), jointly with market entry and location decisions (Hastings, 2004; Iyer and Seetharaman, 2005; Mazzeo, 2002). To contribute to this literature, I estimate how various simultaneous factors, including market characteristics, firm characteristics, and competition, drive manager decisions in the airline industry.

The estimation technique used in this paper stems from economics and marketing research on static discrete game estimation. Similar estimations have addressed research problems related to market entry and location choices (e.g., Vitorino, 2012; Zhu, Singh and Dukes, 2011), retailer pricing strategies (Ellickson and Misra, 2008), and group purchase decisions (Hartmann, 2010). The key feature of these research problems is that the decision maker chooses an action from an action set, taking into consideration the choices of other decision makers (e.g., competitor, peer consumer). I make use of these recent state-of-the-art developments in models of the supply side to gain insights about the actions of firms and how the competitive environment affects the service quality levels in the airline industry.

3.3. Background Information: On-Time Performance in Airline Industry

Flight cancellation and flight delay may be caused by many factors. Some of these factors can not be controlled by firms, such as bad weather, airport congestion, and national secu-
rity concerns. However, according to statistics provided by BTS (Bureau of Transportation Statistics), around 60% of flight cancellations and delays are caused by controllable reasons, such as mechanical problems, shortage of gate slots, crew out-of-time and late aircraft arrivals. All of these reasons are closely related to a tradeoff firms constantly face - improving on-time performance and service quality vs. reducing cost of operational resources.

A firm’s main operational resources in the airline industry include assigned gate and runway slots in each airport, aircrafts, and crews. A firm’s gate and runway slots in each airport are assigned by FAA (Federal Aviation Association) at a semi-yearly or yearly base, and thus are limited resources. Aircrafts are costly to purchase, lease or maintain. Crew salaries and benefits also cost firms a substantial amount of money. In addition, there are strict rules about the maximal amount of time a crew, especially a pilot can serve daily, as well as the minimal number of breaks a crew should have monthly. Due to the substantial amount of costs of adding additional aircrafts and crews, firms tend to maximize their aircraft and crew utilization, which means, to let aircrafts and crews serve as many flights as possible. Given the limited number of assigned gate and runway slots, aircrafts, and crews firms implement complicated algorithms to route their aircrafts and crews in a way that maximally satisfies the flight service needs and in the meanwhile minimizes costs.

The routing plans suggested by algorithms work well at “ideal conditions”, that is, when there are no interruptions from the runway/gate congestion, crew sickness/strikes, aircraft wear-outs, etc. In reality, however, these interruptions often happen. For example, the line of flights awaiting to take off is longer than expected, and in the meanwhile, one of the pilots runs out of the allowed service time and is forced to stop his/her duty if the flight has not taken off. Under this circumstance, if there is no back-up pilot arriving on time, the flight has to be delayed or cancelled. If a crew is sick when s/he is about to serve a flight duty and there are no backup crews arriving on time, the flight is likely to be delayed or cancelled. Similarly, if the aircraft happens to have mechanical problems before taking off, and the firm cannot assign a back-up aircraft on time, the flight will be delayed or even cancelled. It seems that backup crews and aircrafts may solve these problems in most cases, but these resources are costly, and firms usually cannot afford the luxury of having sufficient backup resources. In addition, we may wonder that if firms do regular mechanical inspections during
breaks of aircrafts flight services, they may avoid most of the mechanical problems before aircrafts take off. But the problem is firms tend to fly their aircrafts as much as they can to save costs, so it is not feasible to provide the regular mechanical inspection to every aircraft during its service breaks.

The scenarios described above are common issues that cause flight cancellations and flight delays. However, if we take into consideration the aircraft and crew routing dynamics, we may see more issues leading to flight cancellations and delays. With the limited number of gate slots, firms tend to schedule as many flights departing from and arriving at a gate as possible. It implies that to ensure perfect on-time performance, all flights scheduled to depart from (arrive at) a gate have to depart (arrive) on-time. If any of the scenarios described above happens, the delayed/cancelled flight will take the gate longer than it should, causing delays of the next scheduled flight to depart from (arrive at) the focal gate. The dynamic aircraft and crew routing also cause potential carry over delays. If a flight is delayed, the aircraft and crews cannot arrive at the destination airport to start the next assigned flight duty, causing delays of the next scheduled flight, and likely delays of the scheduled flight after next. If a firm does not have backup aircrafts and crews to substitute the subsequent scheduled flight duties, one flight delay may cause a sequence of flight delays. This type of delay is named as the late aircraft arrival delay.

When firms encounter unexpected disruptions, and they do not have sufficient backup resources to keep all the scheduled flights on time, they face two choices: to keep the original schedule and delay flights that are subject to the disruptions, or to cancel some flights. These two options each has pros and cons. Delaying flights keeps the scheduled service commitments and does not cause operational burden of rescheduling aircrafts, crews, and passengers, but it may cause carry over delays of subsequent flights (in the same market, or in other markets). Cancelling flights instead, gains the firm sufficient resources (e.g., gate slots, spare aircraft and crews) to keep subsequent flights (in the same market, or in other markets) on time, but it harms the brand image among passengers, as it implies breaking service commitment.

Overall, firms often face the following tradeoffs: to have sufficient backup resources for unexpected disruptions so as to keep good on-time records, or to save costs by fully utilizing
all the available resources; and once they are vulnerable to unexpected disruptions, they will have to decide between cancelling flights and delaying flights. The benefits and costs of each option, are influenced by market and firm characteristics, as well as competitors’ on-time performance.

3.4. Data

3.4.1 Data Description

I collect my data from two sources: the Bureau of Transportation Statistics (BTS) and U.S. Census Bureau. I gather data on delays and cancellations of flights from the On-Time Performance BTS data set. This data set indicates departure delays, measured as the difference in minutes between scheduled and actual departure time; arrival delays, or the difference in minutes between the scheduled and actual arrival time; and cancellations, i.e., whether the flight is cancelled or not. The data are available for each domestic flight operated by firms that earn at least 1% of the total revenue in the airline industry. The cancellation measurement is directly taken from BTS data; consistent with previous literature (e.g., Mazzeo, 2003; Rupp et al., 2006), we use arrival delays to measure on-time performances, because passengers are likely to care more about arrival delay than departure delay.

The T100 Origin and Destination database from the BTS provides additional relevant information for the analysis. This census dataset describes traffic for all domestic origins and destinations by firms with annual revenues greater than $20 million. The included variables are: total passengers served, total number of seats provided, total number of flight departures performed, total number of flight departures scheduled, and distance for each market (route), where a market (route) is a unique origin-destination combination (e.g., Berry and Jia, 2010). I use the total number of flight departures performed and capacity utilization (total number of passengers served/total number of seats provided) to partially determine the firm characteristics. For the market characteristics data (e.g., number of business, income per capita), I turn to the U.S. Census Bureau.

Although BTS maintains data on all 25163 U.S. routes, I restrict the analysis to routes
that satisfy the following criteria: (1) market share larger than 60% for four major airlines (American Airlines, Delta Airlines, United Airlines, Southwest Airlines); (2) the majority of passengers (i.e., greater than 60%) take a direct flight, so that passenger choices are less affected by connecting flights; (3) there is only one major airport in the origin/destination city, to avoid potential airport level competition; and (4) the distance between the origin city and the destination city is greater than 600 miles, to avoid the potential competition from other means of transportation (i.e., car, train, bus). The final sample includes 15 cities, 112 routes, 4 firms, and 71 quarters. The time frame goes from quarter 2 of 1993 to quarter 4 of 2010, producing 9,819 observations in all.

3.4.2 Examples of Service Quality Variation

I select two representative markets (Atlanta-San Francisco and Los Angeles-Denver) to reveal some interesting patterns in the data about the two service quality dimensions, flight delays and cancellations. The first (upper) plot in Figure 3.2 shows the performance of the two major firms, Delta and United, in the Atlanta-San Francisco market. The figure reveals that Delta Airlines had longer average flight delays than United Airlines for all the time under analysis, although after 2004, the differences between the delays of these two firms became smaller. The first (upper) plot in Figure 3.3 shows the rates of flight cancellations for the two firms in the same market. In this case, United Airlines had more frequent flight cancellations than Delta Airlines, and the differences became more apparent after 2004. These patterns suggest that United decreased its level of service quality in this route after 2004, and my model aims at explaining these patterns with changes in market conditions and firm factors.

The Los Angeles-Denver market (see second plots in Figure 3.2 and Figure 3.3) presents a unique situation that is somewhat common in the dataset. United Airlines held a monopoly before 2000 until the entry of American Airlines. When American Airlines entered, United reduced its average delay minutes and cancellation rate over 2000 and 2001. In 2008, Southwest Airlines also entered this market. We observe that both United Airlines and American Airlines decreased their average delay minutes at the time of the entry, suggesting some competitive response to the presence of the new entrant. The model I propose takes into account the possibility of competitive reactions to explain the levels of service quality.
Figure 3.2: Evolution of delay (in minutes), in two markets: Atlanta-San Francisco and Los Angeles-Denver

Notes: The first (upper) plot shows that in market Atlanta-San Francisco, Delta Airlines had longer average flight delays than United Airlines for all the time under analysis. The second (lower) plot shows that in market Los Angeles-Denver, United Airlines decreased its delay at the entry of American Airlines, and at the entry of Southwest Airlines, both United Airlines and American Airlines decreased their delays.

3.4.3 Model-Free Evidence of Market, Firm, and Competitive Characteristics

In this section, I describe some of the data that I use to explain the decisions on service quality, namely market, firm, and competitive characteristics, and provide some model-free insights. Starting with state income per capita, I categorize income per capita into two groups, (i.e., I calculate the median value of income per capita cities included in the sample for each year, and median-split the cities into two groups, high and low, for each year) and compare the means of flight cancellation rates (i.e., fraction of cancelled flights out of total flights). The left plot in Figure 3.4 shows that the average cancellation rate
Figure 3.3: Evolution of cancellation rate (in fraction of total flights), in two markets: Atlanta-San Francisco and Los Angeles-Denver

Note: The first (upper) plot shows that in market Atlanta-San Francisco, United Airlines had more frequent flight cancellations than Delta Airlines, and the differences got more apparent after 2004. The second (lower) plot shows that in market Los Angeles-Denver, United Airlines decreased its cancellation rates after the entry of American Airlines, and before the entry of Southwest Airlines, both United Airlines and American Airlines decreased their cancellation rates.

is higher in markets with high state income per capita than in the low state income per capita group, which offers a counter intuitive pattern. We would expect instead that firms provide better services in markets with high income per capita. However, if we take a close look at the cities with low and high state income per capita, we can better understand the pattern. Several cities with low income per capita (at the state level), including Atlanta, Dallas, St. Louis, Phoenix, Miami, and Tampa, are busier, larger, and more complex air transportation centers, where flight cancellations may lead to very negative impacts due to the large volume of passengers, flights, and connections to be handled. Additionally, these are also cities located in the south of the United States, where the weather is rarely the cause
Figure 3.4: Cancellation rate (fraction of cancelled flights out of total flights) for two groups of markets, divided by income per capita and the existence of a competitor’s hub.

Note: The average cancellation rates are lower in cities with low state income per capita, than in cities with high state income per capita; the average cancellation rates are lower when the competitor does not have a hub in the market, than when the competitor has a hub in the market.

of flight cancellations. These two factors explain some of these differences in cancellation rates and should be taken into account when modeling the service quality decisions.

I am also interested in understanding whether service quality decisions are influenced by the presence of a competitor’s hub in the market. I split the sample according to whether there was a competitor’s hub in the market and compare the means of cancellation rates in these two samples (see the right plot in Figure 3.4). This mean is lower when a competitor does not have a hub in the market, showing that firms seem to provide better services when competitor(s) do not have a hub in the market.

The number of quarterly flight departures and capacity utilization of a firm in each market represent two key firm characteristics. I median-split observations by the number of flight departures for each market (i.e., route), group the number of flight departures into high and low levels, and then again compare the means of the cancellation rates (see Plot 1 in Figure 3.5). The mean cancellation rate values indicate that firms are more likely to have a high flight cancellation rate when they also offer a large quantity of flights. The categorization according to capacity utilization (i.e., median-split observations by capacity utilization for each market) reveals that the mean cancellation rate in the high capacity utilization group is lower than that in the low capacity utilization group (see Plot 2, Figure 3.5), suggesting that firms are unlikely to cancel their flights when most of their flight seats are taken. Regarding
Figure 3.5: Cancellation rate for two group of firms based on firm characteristics: number of departures performed, capacity utilization, and hub destination.

Note: The average cancellation rates are lower when the number of quarterly flight departures are low than when the number of flight departures are high; the average cancellation rates are lower when the capacity utilization is low than when the capacity utilization is high; the average cancellation rates are lower when the destination airport is not a hub than when the destination airport is a hub.

the existence of own hub, Plot 3 in Figure 3.5 suggests that mean of cancellation rate is higher when the destination is a firm’s own hub, compared to when the destination is not a hub.

As an example of competitive response, I use the Los Angeles-Denver market, where incumbent(s) seemed to react to a new entrant by adjusting their service quality levels. I compare the changes in average delay (in minute) and cancellation rates across a group of markets with and without Southwest. Southwest entered the Boston-Denver market in the first quarter of 2010 but was not present in some other markets originating from Boston. I compute the mean average delay and mean cancellation rates of incumbent firms before and after the entry of Southwest in the Boston-Denver market against those of the incumbent firms before and after the first quarter of 2010 (when Southwest entered the Boston-Denver market) for other markets that originated in Boston without the presence of Southwest (see Figure 3.6). With the presence of Southwest, I observe that the mean average delays and cancellation rates declined more in the Boston-Denver market than in markets in which Southwest never entered.

I provide descriptive statistics about the measurements of service quality and the independent variables in Table 3.1. The average flight cancellation rate was 1.4%, while the
Figure 3.6: Incumbents’ Service Quality Reaction to Southwest Entry: Origin Boston

Note: Incumbent firms’ average delay and cancellation rates drop more after the first quarter of 2010 (when Southwest entered the market Boston-Denver) in Boston-Denver, than in other markets where Southwest never entered.

average delay was 11.8 minutes, with a large dispersion across markets, firms, and time. In the analysis, I use the median-centered values of flight cancellation rate and average delay for each market to capture the relative performance of each firm and control for weather and location of market that might affect the absolute level of service quality. The markets included in the data also exhibit large variation in terms of the number of businesses and income per capita. These variations may be due to market differences, economic growth and inflation over time. I use the yearly median-centered values of number of businesses and income per capita in discretization and estimations to account for economic growth/inflation over time.
Table 3.1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service Quality</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Flight Delay (minute)</td>
<td>11.84</td>
<td>5.27</td>
<td>0.45</td>
<td>55.16</td>
</tr>
<tr>
<td>Average Flight cancellation Rate (percentage)</td>
<td>1.4%</td>
<td>1.8%</td>
<td>0%</td>
<td>21.5%</td>
</tr>
<tr>
<td>Market Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Businesses (geometric mean of the origin and destination cities)</td>
<td>87,512</td>
<td>28,052</td>
<td>46,363</td>
<td>181,246</td>
</tr>
<tr>
<td>Income per Capita (geometric mean of the origin and destination states)</td>
<td>32,657</td>
<td>6,904</td>
<td>1,885</td>
<td>47,886</td>
</tr>
<tr>
<td>Presence of Competitor’s hub in the market</td>
<td>0.47</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Firm Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>457.59</td>
<td>332.40</td>
<td>30</td>
<td>1,827</td>
</tr>
<tr>
<td>Average Capacity Utilization (percentage)</td>
<td>0.74</td>
<td>0.11</td>
<td>0.30</td>
<td>0.97</td>
</tr>
<tr>
<td>Whether the Origin City is a Hub of the Focal Firm</td>
<td>0.48</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Whether the Destination City is a Hub of the Focal Firm</td>
<td>0.48</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

3.5. Model

3.5.1 Justification for Assumptions

The delay and cancellation levels of each firm in each market are closely related to the firm’s flight scheduling decisions, which involve fleet assignments, block time scheduling, crew assignments, and so on, coordinated over all markets (i.e., routes) in the firm’s flight network. Flight scheduling is a complex optimization problem, solved by algorithms (e.g., Sohoni, Lee and Klabjan, 2008), but in practice, firms strategically apply the results generated by algorithms and decide how much resources (i.e., the length of block time, the number of crew assigned) to allocate to each market (e.g. Gopalakrishnan and Johnson, 2005), based on the market conditions and competitive intensity. With this model, I aim to infer how different factors drive firms’ strategic decisions on flight cancellation rates and average flight delays in each market. Firms focus mainly on the total profits from their route networks when scheduling flights, however, they may still try to extract the most profits from each large market (i.e., route) they serve. All markets (i.e., routes) in the data set are large markets, I therefore consider it proper to assume that firms make service quality decisions in each market to maximize their market profits. Many firms also adjust the block time, fleet and
crew assignments seasonally (i.e., 2-3 months) (Centeno and Vitt, 2011; Sinnott, 2002), thus, I model firms’ service quality as a quarterly decision.

My goal is to explain the decisions firms make regarding their service quality across multiple markets. The choice of service quality can be framed as a game among a finite set of players. Given the competitive environment of the industry, the profits of each firm depend on the actions of other firms, which are taken into consideration when making decisions. Therefore, I assume that each firm chooses the service quality that maximizes its expected profits in each market in each quarter\(^2\).

I do not have precise revenue/market share measurements for each firm in each market at each quarter. Thus, consistent with previous literature (e.g., Berry, 1992; Mazzeo, 2002) I need to use demand and cost shifters to approximate a reduced form specification of profits. Market characteristics (i.e., potential demand) are likely to shift the demand, firm characteristics (i.e., capacity utilization) are likely to drive the cost of each service quality action, and firm’s expectations of competitors’ actions may also influence the profits of each service quality action. I therefore use these variables related to these three factors to represent profits.

### 3.5.2 Intuitions Behind the Model

Each firm chooses a service quality level that maximizes its profits in a market at a time. As explained in the last paragraph in section 3.4.1, the focal firm’s profits of choosing a service quality level depend on market characteristics, firm characteristics, and competitors’ actions. In addition, some random elements, such as the mechanical problems of airplane engines, the relationship between the focal firm and its labor union, may also influence the profits. If the random elements are drawn from a known distribution, the probability of the focal firm choosing each service quality level can be computed.

In each time period, firms in the same market choose service quality levels simultaneously.

---

\(^2\)Note that I model firms’ choice of service quality as a static game. I am aware that service quality decisions may have long-term impacts. However, from conversations with airline executives, we realized that firms in general only consider short-term profits (recent quarter or semi-year) when making strategic decisions, because their operational resources (i.e., runway slots, airport gates) assigned by Federal Aviation Association (FAA) change at a semi-year base, making long-term planning difficult. I believe a static model is good representation to capture how decisions are made in the industry.
That is to say, the focal firm is not able to see the service quality levels its competitors choose when it makes its own service quality decision. As a result, the focal firm makes a rational inference (i.e., a belief) about competitors’ choices. The focal firm is unlikely to observe its competitors’ random elements; therefore, the focal firm can only have beliefs about the service quality choice probabilities of its competitors.

If all firms make rational inferences about their competitors’ service quality choices (i.e., an equilibrium condition is achieved), the expected choice probabilities of competitors, which enter the focal firm’s profit functions, have to be consistent with the competitors’ actual choice probabilities; and competitors’ actual choice probabilities are also functions of the focal firm’s choice probabilities. The competition component in the profit function is therefore endogenous. To address the endogeneity of expected competitors’ service quality choices, and to account for firms’ rational expectations about each other’s service quality choices, I need to estimate firms’ service quality choices as a system of simultaneous discrete choice models.

3.5.3 Formal Specification of the Model

I observe firms \( f = 1, 2, \ldots, F \) serving markets \( m = 1, 2, \ldots, M \) at time \( t = 1, 2, \ldots, T \). A firm’s service quality choice for market \( m \) at time \( t \) is denoted as \( a_{fmt} \), which can take any discrete level in the action set \( k = 1, \ldots, K \). The competitors’ service quality actions are denoted \( a_{-fmt} = (a_{1mt}, \ldots, a_{(f-1)mt}, a_{(f+1)mt}, \ldots, a_{Fmt}) \).

Each firm makes a service quality decision in each market it serves, maximizing its local (market) profits

\[
\pi_{fmt} = \Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt}) + \epsilon_{fmt},
\]

(3.1)

where \( \Pi_{fmt} \) is a known and deterministic function of the state vector \( s_{fmt} \) defined below, the focal firm’s action \( a_{fmt} \), and the competitors’ actions \( a_{-fmt} \). The term \( \epsilon_{fmt} \) denotes a private shock that affects the profits of firm \( f \) in market \( m \) at time \( t \). As \( \epsilon_{fmt} \) is private information for each firm, each firm makes decisions based on its own state vector, \( s_{fmt} \), its competitors’ state vectors, \( s_{-fmt} \), its own private shock, \( \epsilon_{fmt} \), but not its competitors’ private shock \( \epsilon_{-fmt} \). Thus, I define each firm’s decision rule as \( a_{fmt} = d_{fmt}(s_{fmt}, s_{-fmt}, \epsilon_{fmt}) \).
where choices are a function of the state vectors and its own shock, but not the shocks of the competitors. Without knowing the exact value of each firm’s private shock, what a firm (or an econometrician) can infer about other firms are their probabilities of taking each action, which depend on the state vectors and the distribution of the private shocks. That is to say, from both the firms’ and the econometrician’s perspective, the probability that a given firm chooses action \( a \), conditional on the state vectors, is

\[
\Pr(a_{fmt} = a|s_{fmt}, s_{-fmt}) = \int 1\{d_{fmt}(s_{fmt}, s_{-fmt}, \epsilon_{fmt}) = a\} f(\epsilon_{fmt}) d\epsilon_{fmt}, \tag{3.2}
\]

where \( 1\{d_{fmt}(s_{fmt}, s_{-fmt}, \epsilon_{fmt}) = a\} \) is an indicator function equal to 1 if firm \( f \) in market \( m \) at time \( t \) chooses action \( a \) and 0 otherwise. Let \( \mathbf{P}_{fmt} \) denote the set of these probabilities of all firms in market \( m \) at time \( t \) and all choice alternatives. Note that the focal firm’s payoffs from taking each action depends on competitors’ actions, but all what the focal firm knows about competitors are their probabilities of taking each action. The focal firm’s expected payoffs therefore depend on three components: the deterministic function of the state vector, \( \Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt}) \), the probability of each competitor taking each action, \( \Pr(a_{-fmt} = a|s_{-fmt}, s_{fmt}) \), and the private shock, \( \epsilon_{fmt}(a) \). Mathematically, the expected profits for firm \( f \) if it chooses action \( a \) in market \( m \) at time \( t \) (taking the influence from competitors’ actions into account) is given by

\[
E[\pi_{fmt}(a_{fmt}, s_{fmt}, \epsilon_{fmt}, \mathbf{P}_{fmt})] = E[\pi_{fmt}(a_{fmt}, s_{fmt}, s_{-fmt})] + \epsilon_{fmt}(a) = \sum_{a_{-fmt}} \Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt}) P_{-fmt} + \epsilon_{fmt}(a), \tag{3.3}
\]

where \( P_{-fmt} = \prod_{jmt \neq fmt} \Pr(a_{jmt} \mid s_{jmt}, s_{-jmt}) \). Note that \( P_{-fmt} = \prod_{jmt \neq fmt} \Pr(a_{jmt} \mid s_{jmt}, s_{-jmt}) \) is the products of each competitor’s probability of taking each action (in case there are multiple competitors in the market), and that the term \( \sum_{a_{-fmt}} \Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt}) P_{-fmt} \) is the expected value of \( \Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt}) \), marginalizing out the action probabilities of competitors using \( P_{-fmt} \). Firms choose service quality actions that maximize the expected profits, thus the probability of firm \( f \) taking action \( a \) in market \( m \) at time \( t \) is

\[
\Psi_{a_{fmt}} = \Pr \left( E[\pi_{fmt}(a, s_{fmt})] + \epsilon_{fmt}(a) > E[\pi_{fmt}(a', s_{fmt})] + \epsilon_{fmt}(a'), \forall a' \neq a \right), \tag{3.4}
\]
which is the system of equations that define the Bayesian Nash Equilibrium of the game.

I now specify the functional form of the expected profit functions of firm \( f \) when it chooses service quality \( k \) in market \( m \) at time \( t \). I select three components, related to market characteristics, firm characteristics, and competitive responses. Competitive responses are captured by the expected proportion of competitors choosing each service quality strategy, because the firm should be more worried about how likely each service quality decision is chosen by its competitors, not the identities of competitors taking each service quality decision. Moreover, each service quality action should be associated with some alternative-specific revenues or costs, which are captured by the action specific intercepts. In addition, I also include firm, market, and time fixed effects, because these factors may shift the revenues or cost of taking service quality actions as well. Hence, the expected profit takes the form of

\[
E[\pi_{fmt}(a_{fmt} = k, s_{fmt}, \epsilon_{fmt}, \mathbf{P}_{mt})] = \theta_{0k} + \theta_{fk} + \theta_{mk} + \theta_{tk} + s_{fmt}^M \theta_{Mk} + s_{fmt}^F \theta_{Fk} + \sum_{r=1,...,K} \rho_{fmt}^r \eta_{rk} + \epsilon_{fmt}(k), \tag{3.5}
\]

where \( s_{fmt}^M \) is the state vector of market characteristics of market \( m \) at time \( t \), and \( s_{fmt}^F \) is the state vector of firm characteristics of firm \( f \) in market \( m \) at time \( t \). The term \( \rho_{fmt}^r \) denotes the expected proportion of the focal firm’s competitors who choose service quality strategy \( r \), specifically, \( \rho_{fmt}^r = \frac{1}{(F_{mt} - 1)} \sum_{j \neq f} \text{Pr}_j(a_j = r) \), where \( F_{mt} \) is the number of firms in market \( m \) at time \( t \). Note that all coefficients to be estimated are action specific, which captures that market characteristics, firm characteristics and expected competitors’ actions may influence the profits of each service quality action differently.

If we define \( \Omega = \theta_0, \theta_M, \theta_F, \eta_r \) and assume that \( \epsilon_{fm} \) are are drawn i.i.d. from the Type I Extreme Value distribution across actions and players. The probability that firm \( f \) chooses service quality \( k \) in market \( m \) at time \( t \) is given by

\[
\Psi_{fmt}(a_{fmt} = k \mid \Omega, \mathbf{P}_{mt}) = \frac{\exp(V_k)}{\sum_{k' \in K} \exp(V_{k'})}, \tag{3.6}
\]

where

\[
V_k = \theta_{0k} + \theta_{fk} + \theta_{mk} + \theta_{tk} + s_{fmt}^M \theta_{Mk} + s_{fmt}^F \theta_{Fk} + \sum_{r=1,...,K} \rho_{fmt}^r \eta_{rk}. \tag{3.7}
\]
Let \( \delta_{fmt}(k) \) be an indicator function, such that

\[
\delta_{fmt}(k) = \begin{cases} 
1 & \text{if } a_{fmt} = k \\
0 & \text{if } a_{fmt} \neq k 
\end{cases},
\]

which allows us to construct the likelihood as

\[
Likelihood = \prod_{t \in T} \prod_{m \in M} \prod_{f \in F} [\Psi_{fmt}(a_{fmt} = k \mid \Omega, \mathbf{P}_{mt}, \mathbf{s}_{fmt})]^{\delta_{fmt}(k)},
\]

\[s.t. \mathbf{P}_{mt} = \Psi_{mt}[\Omega, \mathbf{P}_{mt}, \mathbf{s}_{mt}],\]

where \( \Psi_{mt} \) denotes the system of choice probabilities of every firm choosing each possible service quality strategy. This likelihood function involves a system of a discrete choice equations that satisfy a set of fixed point constraints (\( \mathbf{P}_{mt} = \Psi_{mt} \)). I use a two-step approach (i.e., Bajari et al., 2005; Ellickson and Misra, 2008) to estimate the parameter vector \( \Omega \). The first step obtains consistent estimates of each firm’s beliefs about the strategic actions of its competitors; in the second, likelihood maximization step, these “beliefs” help estimate the parameters of interest.

3.6. Model Identification and Estimation Method

3.6.1 Conditions for Identification

The insights for my identification strategy are mainly borrowed from the static game literature (i.e., Bajari, Hong, Krainer and Nekipelov, 2010) for which three assumptions must be satisfied. First, the private information (\( \epsilon \)) has to be distributed i.i.d. across players and actions in any market and has to be drawn from a distribution of known parametric form. Second, the expected profit of one strategy has to be normalized to 0, consistent with the standard identification condition of any multinomial choice model. I normalize the expected profits of the lowest level of service quality (i.e. high cancellation rates and high average delay minutes) to be 0. These first two assumptions enable us to identify the expected profit function \( E[\pi_{fmt}(a_{fmt}, s_{fmt})] \). Third, an exclusion restriction must be satisfied to identify the
deterministic part of the profit function (i.e., $\Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt})$), given choice probabilities and expected profits $E[\pi_{fmt}(a_{fmt}, s_{fmt})]$. The relation between $\Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt})$ and $E[\pi_{fmt}(a_{fmt}, s_{fmt})]$ can be written as

$$E[\pi_{fmt}(a_{fmt}, s_{fmt})] = \sum_{a_{-fmt}} \Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt}) P_{-fmt},$$

(3.10)

where $P_{-fmt} = \Pi_{jmt\neq fmt} \Pr_{jmt}(a_{jmt} | s_{jmt})$.

The identification of $\Pi_{fmt}(s_{fmt}, a_{fmt}, a_{-fmt})$ then is equivalent to a problem of finding a solution to the system of equations in Equation 3.10. The choice probability of each firm is a function of its beliefs regarding the conditional probabilities of its rivals, as well as state variables. If firms share exactly the same value for each state variable, this system of equations, which is not full rank, cannot be solved, because the number of unknowns are more than the number of informative equations. To solve this system of equations, I must ensure that there are one or more covariates that enter the payoff function of firm $f$ in market $m$ at time $t$ but do not enter the payoff functions of other firms in the same market at the same time, or the payoff functions of firm $f$ in other markets at other time. Among the state variables we have, departures performed and capacity utilization vary across firms, markets and time. That is to say, values of these state variables are different across firms in the same market at the same time, and for each firm, values of these state variables are different across markets and time as well. Moreover, I include firm, market, year, and quarter fixed-effect terms in the payoff functions, which further guarantee the uniqueness of each equation in the system. This system of equations is a full rank matrix, thus the coefficient of a state variable can be identified by the variation of the focal variable and the corresponding variation of the service quality choice in the data. Specifically, the coefficients of departures performed and capacity utilization can be identified by the variation of service quality choice at the firm-market-time level in response to variations of these state variables at the firm-market-time level. The coefficients of hub of origin and hub of destination can be identified by the service quality choice variation at the same time in different firm-market units, in response to variations of these state variables at across firm and market. The coefficients of the state variables which vary at the market level (i.e., number of business, income per capita, and
competitor’s hub), can be identified by the service quality choice variation of the same firm in different market-time units, in response to the variation of these state variables across markets and time.

3.6.2 Existence and Multiplicity of Equilibria

The existence of equilibria is ensured if the system of equations given by Equation 3.6 has at least one solution. The choice probabilities $\Psi$ are monotonic, continuous, and strictly bounded within the set $(0, 1)$, given the Type I Extreme Value distribution assumption about $\epsilon$. The existence of solutions to the system of equation then follows, according to Brower’s Fixed Point Theorem (McKelvey and Palfrey, 1995).

It is possible that multiple equilibria exist (i.e., multiple solutions to the system of equations given by Equation 3.6). To remedy this potential challenge I: (1) include firm fixed effects to make the game asymmetric (i.e., the set of profits earned when United chooses high service quality while Southwest chooses low service quality is different from the set of profits earned when United chooses low service quality while Southwest chooses high service quality), such that I can recover at least the estimates of a dominant equilibrium (i.e., an equilibrium most likely to happen); (2) impose a standard assumption in two-step methods for estimating incomplete information games, which states that given a set of value of $\Omega$ and $X$, players (or nature) select only one equilibrium from all possible equilibria; and (3) assume that firms do not switch to other equilibria as long as $\Omega$ and $X$ do not change (i.e., Vitorino 2012).

3.6.3 Endogeneity

Table 3.2 presents a list of the variables used to define the state of each firm. For market characteristics, we use measurements of the size and value of the market, such as the number of businesses and income per capita. Additionally, I also include a dummy variable that tracks if the market is a hub for a competitor. For firm characteristics, I use measurements that correlate with costs and/or revenues, such as the volume of flight departures performed and capacity utilization. Finally, it is likely that the decisions regarding service quality might
Table 3.2: Variables that Define the State Space

<table>
<thead>
<tr>
<th>State Variable</th>
<th>Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Characteristics</td>
<td>Geomean of Number of Businesses</td>
</tr>
<tr>
<td></td>
<td>Geomean of Income per Capita</td>
</tr>
<tr>
<td></td>
<td>Whether there is a hub of a Competitor in the market</td>
</tr>
<tr>
<td>Firm Characteristics</td>
<td>Total Number of Flight Departures</td>
</tr>
<tr>
<td></td>
<td>Average Capacity Utilization</td>
</tr>
<tr>
<td></td>
<td>Whether the Origin city is a Hub of the Focal Firm</td>
</tr>
<tr>
<td></td>
<td>Whether the Destination city is a Hub of the Focal Firm</td>
</tr>
</tbody>
</table>

be affected if the route includes a hub for the focal firm, and so I include two additional variables that take the value of one if the origin or the destination airport is a hub for the focal firm, and zero otherwise.

The setup of the static discrete game naturally accounts for the simultaneity of players’ strategy choices (i.e., competition shocks), which is one major source of endogeneity (Cornwell and Trumbull, 1994). However, I am aware that some of the state variables are potentially endogenous. For example, the number of flight departures performed and capacity utilization may be endogenous because firms may consider an unobserved component that affects both the decision of the number of flights and the decision about the service quality. To reduce these endogeneity concerns, I include firm, region, year, and quarter fixed effects (as in Ellickson and Misra (2008)). These fixed effects absorb most variations caused by unobservable firm/market/time level factors, thereby making the error term close to orthogonal to the state variables.

3.6.4 Estimation Method

I use a two-step approach (i.e., Bajari et al., 2005; Ellickson and Misra, 2008) to estimate the parameter vector $\Omega$. The first step is to non-parametrically recover $\widehat{Pr}_{fmt}(a_{fmt} | s_{fmt})$, that is, the estimates of beliefs of firm $f$ in market $m$ at time $t$ about the conditional choice probabilities of its competitors. Specifically, within each dimension of the state space (i.e., a unique combination of state variables), I obtain the probability of each firm choosing each service quality level from the data. I then have firms’ beliefs about each of its competitors’ probabilities of making each service quality decision, given the state space, and construct
the beliefs of competitors’ aggregated service quality decision probabilities $\hat{\rho}^r_{fmt}$, where $r = 1, ..., K$, for each firm $f$ in each market $m$ at each time $t$. Knowing $\hat{\rho}^r_{fmt}$, we proceed the second step, which is to choose the parameters that maximize the following likelihood function

$$L(\Omega) = \prod_{t \in T} \prod_{m \in M} \prod_{f \in F} [\Psi_{fmt}(a_{fmt} = k \mid \hat{P}_{mt}, s_{fmt})]^{\delta_{fmt}(k)},$$

where $\hat{P}_{mt}$ denotes the set of estimated choice probabilities (i.e., belief) of all firms in market $m$ at time $t$ (including the probabilities of every firm in the focal market taking every possible service quality action). I use the in-sample predictions from the maximum likelihood estimation to update firms’ beliefs on competitors’ service quality probabilities, and then perform the maximum likelihood estimation with the updated beliefs. I proceed with these two steps iteratively until I achieve consistent estimates of $\Omega^3$.

### 3.7. Results

In the model section, I conceptualize firms’ service quality choices as $K$ discrete levels. In practice, I implement the service quality choices to be four levels: high cancellation and high delay, high cancellation and low delay, low cancellation and high delay, low cancellation and low delay. I present results of robustness checks to show that the four-level discretization does not change the results qualitatively.

#### 3.7.1 Analysis of Parameter Estimates

I present the estimation results in Table 3.3.\textsuperscript{4} In terms of market characteristics, I find that the number of businesses increases the likelihood that firms adopt a high quality level, with a low cancellation, low delay service (the expected multinomial log-odds for the low cancellation low delay service, relative to the high cancellation high delay service increase by

\textsuperscript{3}Consistent estimates are defined as converged estimates between the last two rounds of iteration. The convergence criterion is $|\Omega^{t+1} - \Omega^t| < 1.0E^{-8}$.

\textsuperscript{4}The profits of the high cancellation, high delay service quality decision are normalized to 0 for identification.
0.154). Potential demand from business passengers increases with the number of businesses in the market, and firms may try to maintain their flight schedules and arrive on time to ensure their business passengers do not miss their appointments. Income per capita reduces the likelihood of adopting the low cancellation and low delay service though (the expected multinomial log-odds for the low cancellation low delay service decrease by 0.359), as well as the low cancellation, high delay service (the expected multinomial log-odds for the low cancellation high delay service decrease by 0.325), matching my discussion in the model-free section. As previously discussed, firms have lower cancellation rates when the income per capita is low in the market, related to the presence of hubs in low income per capita areas, as well as their relatively less severe weather. If there is a competitor’s hub in the market, the focal firm is unlikely to provide low cancellation, low delay service (the expected multinomial log-odds for the low cancellation low delay service decrease by 0.428). The presence of a hub provides the competitor with advantages in attracting and locking in passengers, making it difficult for the focal firm to compete. This seems to prompt the focal firm to choose not to allocate service-related resources to those market.

Regarding firm characteristics, the results show that the number of flight departures negatively influences the likelihood of choosing low cancellation, low delay and low cancellation, high delay services (the expected multinomial log-odds for the low cancellation low delay service decrease by 0.112, and the expected multinomial log-odds for the low cancellation high delay service decrease by 0.246). It seems that firms are reluctant to improve their service quality when they supply a large quantity of flights, which already attract passengers through the flexibility offered. Moreover, since with a large number of flight supplied it is relatively costless to rebook passengers from the cancelled flights, firms are more prone to cancel flights. Capacity utilization increases the likelihood of choosing low cancellation, low delay and low cancellation, high delay services (the expected multinomial log-odds for the low cancellation low delay service increase by 0.295, and the expected multinomial log-odds for the low cancellation high delay service increase by 0.593), whereas it decreases the likelihood of the high cancellation, low delay service (the expected multinomial log-odds for the high cancellation low delay service decrease by 0.251). The results suggest that firms tend to keep their flight commitment (i.e., low cancellation) and improve their on-time performance
(i.e., low delay) when they are able to manage their capacity well. If they cannot do well by
decreasing both cancellation and delay, at least they try to keep their service commitment
(i.e., low cancellation), in order to not impact a large number of passengers in a fully or close
to fully booked flight. Finally, the results related to the existence of hub effects suggest that
it is costly for firms to provide high service quality in their hubs (when departing from a
hub, the expected multinomial log-odds for the low cancellation low delay service decrease
by 0.637, the expected multinomial log-odds for the low cancellation high delay decrease
by 0.189, and the expected multinomial log-odds for the high cancellation low delay service
decrease by 0.278; when flying to a hub, the expected multinomial log-odds for the low can-
celation high delay service decrease by 0.463, and the expected multinomial log-odds for
the low cancellation high delay service decrease by 0.566), probably because they have busy
and complex patterns of scheduling with flights coming from and going to places in their
networks, leading to shortages of resources (i.e., airport gates, runway slots).

I complete my discussion of the results by discussing the effect of competitors’ choices
on the decision of the service quality level. Here, the main finding is that I find evidence of
differentiation strategies by the firms. When firms believe that competitor are more likely to
provide a high service quality of low cancellation, low delay services, the focal firm is likely to
provide the opposite low level of service quality with high cancellations and high delays (the
expected multinomial log-odds for the low cancellation low delay service, relative to the high
cancellation high delay service, decrease by 1.022, the expected multinomial log-odds for the
low cancellation high delay service decrease by 1.914, and the expected multinomial log-odds
for the high cancellation low delay service decrease by 1.255). Instead of being motivated,
firms seem reluctant to improve their service quality to match their competitor who already
maintain their service commitment and provide good on-time performance, probably because
the focal firm would have to allocate significant resources to reach this level of service quality.
Additionally, firms are likely to provide high service quality (low cancellation, low delay)
when they believe their competitors are likely to perform poorly in one of the dimensions.
That is, one unit increase in competitors’ probability of providing high cancellation low delay
services (low cancellation high delay service) increases the expected multinomial log-odds for
low cancellation low delay service (of focal firm) by 0.921 (2.2). In other words, firms are
motivated to provide good services in both dimensions when competitors provide good service in one dimension but poor service in the other, as a way to differentiate themselves from the competition. Finally, the focal firm probably adopts a high cancellation, low delay service if it believes its competitors are going to offer high delay, low cancellation and/or low delay, and high cancellation services. Specifically, one unit increase in competitors’ probability of providing high cancellation low delay services (low cancellation high delay service) increases the expected multinomial log-odds for low cancellation low delay service (of focal firm) by 0.99 (2.395). However, the likelihood of providing high delay, low cancellation service is not affected by firms’ beliefs about their competitors’ service quality decisions. These results suggest that firms are likely to work on their on-time performance but not change how well they keep their flight commitments in a market when they are threatened by their competitors’ service performance.

3.7.2 Discussion of Drivers of Service Quality Decisions

In section 3.7.1, I discussed the effects of market characteristics, firm characteristics, and competition on the joint decision of flight cancellations and delays. However, it is not clear whether firms follow different decision processes to determine the level of flight cancellation and the level of flight delay. To provide in-depth insights on service quality decisions, I discuss drivers of flight cancellation and drivers of flight delay individually, and seek to find differences in the decision processes for these two service dimensions.

I list the state variables that significantly influence the flight cancellation decision in Table 3.4. In our data, most markets with low income per capita are important air transportation centers (e.g., Atlanta, Dallas, Miami) or are located in the south, whereas many markets with high income per capita are not air transportation centers and/or are located in the north (e.g., Boston, Baltimore, Minneapolis). The results suggest that firms tend to not cancel many flights in air transportation centers located in the south, the result is consistent with the intuitions that firms cancel more flights in markets that are not important and that the weather conditions drive flight cancellations.

Firms are also likely to cancel more flights (1) as their supply of flights increases and (2) when they have a hub airport in the market. They are not likely to cancel flights as
Table 3.3: Parameter Estimates

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Cancel + Low Delay</th>
<th>Low Cancel + High Delay</th>
<th>High Cancel + Low Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.324***</td>
<td>1.465***</td>
<td>-0.437*</td>
</tr>
<tr>
<td></td>
<td>(0.199)</td>
<td>(0.206)</td>
<td>(3.33)</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>0.154**</td>
<td>-0.005</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td>(0.080)</td>
<td>(0.081)</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>-0.359***</td>
<td>-0.325**</td>
<td>-0.039</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td>(0.105)</td>
<td>(0.103)</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.428***</td>
<td>-0.072</td>
<td>0.132</td>
</tr>
<tr>
<td></td>
<td>(0.156)</td>
<td>(0.177)</td>
<td>(0.172)</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>-0.112*</td>
<td>-0.246***</td>
<td>-0.060</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.069)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>0.295***</td>
<td>0.593***</td>
<td>-0.251***</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.067)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Hub Origin</td>
<td>-0.637***</td>
<td>-0.189**</td>
<td>-0.278***</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.096)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>-0.463***</td>
<td>-0.566***</td>
<td>0.146</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.096)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-H Probability</td>
<td>0.019</td>
<td>-0.179</td>
<td>-0.147</td>
</tr>
<tr>
<td></td>
<td>(0.418)</td>
<td>(0.437)</td>
<td>(0.432)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-L Probability</td>
<td>0.921*</td>
<td>0.823</td>
<td>0.990**</td>
</tr>
<tr>
<td></td>
<td>(0.475)</td>
<td>(0.517)</td>
<td>(0.471)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-H Probability</td>
<td>2.200***</td>
<td>0.837</td>
<td>2.395***</td>
</tr>
<tr>
<td></td>
<td>(0.518)</td>
<td>(0.557)</td>
<td>(0.548)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-L Probability</td>
<td>-1.022**</td>
<td>-1.914***</td>
<td>-1.255**</td>
</tr>
<tr>
<td></td>
<td>(0.471)</td>
<td>(0.518)</td>
<td>(0.506)</td>
</tr>
</tbody>
</table>

Notes: H and L refer to high and low, presented as cancellation and delay, in that order.
Standard errors are in parenthesis.
* p < 0.10. ** p < 0.05. *** p < 0.01.

their aircraft capacity utilization increases. We can infer from these results that the flight cancellation decision relates closely to capacity management and scheduling flexibility. Firms are unlikely to cancel flights when it is profitable to let their aircrafts take off (i.e., most of seats are sold). When firms have large flight supply in a market, they have the flexibility to reschedule passengers to the next flights. Similarly, when firms have a hub in the market, they can more flexibly reschedule passengers when they cancel some flights. The convenience of rescheduling makes firms more likely to cancel some flights.
Table 3.4: State Variables and Cancellation Decision

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Cancel + Low Delay</th>
<th>Low Cancel + High Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income per Capita</td>
<td>-0.359***</td>
<td>-0.325**</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>-0.112*</td>
<td>-0.246***</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>0.295***</td>
<td>0.593***</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Hub Origin</td>
<td>-0.637***</td>
<td>-0.189**</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>-0.463***</td>
<td>-0.566***</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-L Probability</td>
<td>-1.022**</td>
<td>-1.914***</td>
</tr>
<tr>
<td></td>
<td>(0.471)</td>
<td>(0.518)</td>
</tr>
</tbody>
</table>

Notes: H and L refer to high and low, presented as cancellation and delay, in that order. Standard errors are in parenthesis.
* p < 0.10. ** p < 0.05. *** p < 0.01.

Firms also tend to cancel more flights when the competitors provide good services in both dimensions, which signals that this market is important for the competitors. If the market is important for the competitors, the focal firm has to compete intensively to increase the level of its demand. That is, it is likely that the focal firm cannot obtain substantial revenue payoffs, even if it improves its service quality in the market, so it is more likely to save its service-related resources and allocate them to other markets.

I list the state variables that significantly influence the flight delay decision in Table 3.5. Firms are unlikely to provide good on-time services (i.e., low delay) when they depart from their hub airports. This result is counterintuitive though, because we would expect that firms have access to a significant proportion of their hub airport resources (e.g., airport gates, runway slots), so they should be able to have good on-time performances. However, firms have complex scheduling issues with aircrafts and crews coming in to and going out of their hubs, their airport resources therefore may not be enough to keep good on-time performances.

Flight delay is driven by competition factors too. Firms are motivated to improve their service quality when their competitors provide good service in one dimension (i.e., flight
cancellation or flight delay). When they respond to competitors’ service decisions, they tend to work on their delays. Firms’ on-time performance in a market depends largely on their operational schedules, such as the relevant aircraft and crew schedules, time block, and so on. These operational schedules are flexible to adjust, compared with the importance or profitability of the market. Firms therefore respond more readily to competitors’ service quality decisions by adjusting their on-time performances. In contrast, firms are unlikely to reduce their flight delays when competitors provide good services in both dimensions. They simply are unlikely to gain any revenue payoffs by improving service quality if the market is important to the competitor, thus they choose to allocate their resources to other markets.

To summarize, the results suggest that flight cancellation and flight delay decisions are driven by different set of factors. Specifically, flight cancellation decisions are influenced mainly by cost-benefit concerns, such as the ease of rescheduling after flight cancellation, the amount of penalty costs (e.g., voucher for food and hotel, brand image damage) from flight cancellation, and the extent of costs saved from cancelling empty flights. These cost-benefit concerns are influenced by the number of flight departures, capacity utilization, and the presence of hub airports in the market. Firms respond to competition by adjusting their flight delay levels such that they are able to differentiate their services from those of competitors. In addition, flight delay decisions are driven by the presence of hub in the origin airport, due to the complicated aircraft and crew scheduling issues in hub airports.

3.7.3 Robustness Checks

To make sure that the results presented in the previous section are not driven by the four-level service quality discretization, I run two sets of robustness checks. In the first robustness check (section 3.7.3.1), I trichotomize the cancellation and delay data (i.e., high, medium, low levels of cancellation and delay) in each market, and estimate the model again using the estimation method proposed in 3.6.4. The data trichotomization enables us to distinguish the good (i.e., low cancellation; low delay) and bad (i.e., high cancellation; high delay) services from those fluctuating in the middle (i.e., medium cancellation; medium delay), and therefore may generate new insights. In the second robustness check (section 3.7.3.2), I run a reduced-form analysis, keeping the original continuous (median-centered) values of the delay
Table 3.5: State Variables and Delay Decision

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Cancel + Low Delay</th>
<th>High Cancel + Low Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hub Origin</td>
<td>-0.637***</td>
<td>-0.278***</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-L Probability</td>
<td>2.200***</td>
<td>2.395***</td>
</tr>
<tr>
<td></td>
<td>(0.518)</td>
<td>(0.548)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-H Probability</td>
<td>0.921*</td>
<td>0.990**</td>
</tr>
<tr>
<td></td>
<td>(0.475)</td>
<td>(0.471)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-L Probability</td>
<td>-1.022**</td>
<td>-1.255**</td>
</tr>
<tr>
<td></td>
<td>(0.471)</td>
<td>(0.506)</td>
</tr>
</tbody>
</table>

Notes: H and L refer to high and low, presented as cancellation and delay, in that order.
Standard errors are in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and cancellation rate variables. If the reduced-form analysis generates similar insights to the main results, I should be confident about the results provided in section 3.7.1.

3.7.3.1 Alternative Service Quality Discretization-Trichotomization

In section 3.7.1, I respectively dichotomize the cancellation and delay data, and implement the service quality choices to be four levels: high cancellation and high delay, high cancellation and low delay, low cancellation and high delay, low cancellation and low delay. I am aware that dichotomization may wash out variations in the data and lose potential insights. Thus, in this robustness check, I trichotomize the cancellation and delay data respectively and estimate the proposed model again. The trichotomization helps us separate the good and bad services from the rest. I implement two sets of thresholds (i.e., 33%-67%, 30%-70%) for trichotomization to avoid generating conclusions from potential biased estimates which are subject to a specific threshold. I only interpret results that are not sensitive to the threshold difference.

The data trichotomization leads to a set of nine-level service quality choices: high cancellation and high delay, high cancellation and medium delay, high cancellation and low delay, medium cancellation and high delay, medium cancellation and medium delay, medium cancellation and low delay, low cancellation and high delay, low cancellation and medium delay, low cancellation and low delay.
and low cancellation and low delay. The size of this choice set makes it difficult to interpret the estimates. To make sure we have a good understanding of the results, I estimate the choice of cancellation (i.e., high cancellation, medium cancellation and low cancellation) and the choice of delay (i.e., high delay, medium delay and low delay) individually, and then estimate the joint choice of cancellation and delay. I provide the estimates and interpretations below.

The parameter estimates of the choice of cancellation levels are presented in Table 3.6 (33%-67% threshold) and Table 3.7 (30%-70% threshold)\(^5\). In terms of market characteristics, income per capita reduces the likelihood of adopting the medium cancellation service, compared to the high cancellation service (the expected multinomial log-odds for median cancellation relative to high cancellation decrease by 0.37 with the threshold 33%-67%, and 0.29 with the threshold 30%-70%). This is consistent with my finding in section 3.7.1. Among the firm characteristics, departing from the hub airport makes firms less likely to adopt medium cancellation services (the expected multinomial log-odds for median cancellation relative to high cancellation decrease by 0.36 with the threshold 33%-67%, and 0.29 with the threshold 30%-70%), and flying into the hub airport makes firms less likely to adopt medium cancellation services (the expected multinomial log-odds for median cancellation relative to high cancellation decrease by 0.63 with the threshold 33%-67%, and 0.52 with the threshold 30%-70%) or low cancellation services (the expected multinomial log-odds for low cancellation relative to high cancellation decrease by 0.35 with the threshold 33%-67%, and 0.34 with the threshold 30%-70%). These results are consistent with those in section 3.7.1, confirming that it is costly for firms to decrease flight cancellations in their hub airports, due to the complex aircraft and crew scheduling in hubs of their networks. The estimates with 33%-67% threshold do not show significant competition effects on firms’ cancellation decisions, whereas the estimates with 30%-70% threshold show that firms are unlikely to provide medium (low) level of cancellation when they believe competitors are likely to provide medium (low) level of cancellation (one unit increase of competitors’ medium cancellation probability decreases the expected multinomial log-odds for medium cancellation relative to high cancellation by 0.4; one unit increase of competitors’ low cancellation probability de-

\(^5\)The profits of the high cancellation decision are normalized to 0 for identification.
Table 3.6: Parameter Estimates: Cancellation-33%-67% Threshold

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Cancel</th>
<th>Medium Cancel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.00</td>
<td>1.92</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>-0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>-0.01</td>
<td>-0.37***</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.18</td>
<td>-0.21</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>-0.10**</td>
<td>0.05</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>0.46***</td>
<td>0.25***</td>
</tr>
<tr>
<td>Hub Origin</td>
<td>-0.13</td>
<td>-0.36***</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>-0.35***</td>
<td>-0.63***</td>
</tr>
<tr>
<td>Belief of Competitors’ H-Cancellation Probability</td>
<td>0.42</td>
<td>0.14</td>
</tr>
<tr>
<td>Belief of Competitors’ M-Cancellation Probability</td>
<td>-0.06</td>
<td>-0.36</td>
</tr>
<tr>
<td>Belief of Competitors’ L-Cancellation Probability</td>
<td>-0.57</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Notes: H, M and L refer to high, medium and low. Standard errors are in parenthesis. 
* p < 0.10. ** p < 0.05. *** p < 0.01.

Increases the expected multinomial log-odds for low cancellation relative to high cancellation by 0.82). Taken together, these results suggest that flight cancellation decisions are weakly driven by competition, and that the weak competition effect shows firms’ tendency to have quality differentiation. These results are consistent with those discussed in section 3.7.1 and section 3.7.2.

The parameter estimates of the choice of delay levels are presented in Table 3.8 (33%-67% threshold) and Table 3.9 (30%-70% threshold)\(^6\). Regarding market characteristics, income per capita negatively drives firms’ likelihood of providing the low delay service (the expected multinomial log-odds for low delay relative to high delay decrease by 0.1 with the threshold

\(^6\)The profits of the high delay decision are normalized to 0 for identification.
Table 3.7: Parameter Estimates: Cancellation-30%-70% Threshold

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Cancel</th>
<th>Medium Cancel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.46</td>
<td>1.95***</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>0.10</td>
<td>0.03</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>0.08</td>
<td>-0.29***</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.24</td>
<td>-0.11</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>-0.07</td>
<td>0.07**</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>0.51***</td>
<td>0.30***</td>
</tr>
<tr>
<td>Hub Origin</td>
<td>-0.15</td>
<td>-0.29***</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>-0.34***</td>
<td>-0.52***</td>
</tr>
<tr>
<td>Belief of Competitors’ H-Cancellation Probability</td>
<td>0.49</td>
<td>0.21</td>
</tr>
<tr>
<td>Belief of Competitors’ M-Cancellation Probability</td>
<td>0.18</td>
<td>-0.40**</td>
</tr>
<tr>
<td>Belief of Competitors’ L-Cancellation Probability</td>
<td>-0.82*</td>
<td>0.41</td>
</tr>
</tbody>
</table>

Notes: H, M and L refer to high, medium and low. Standard errors are in parenthesis.

* p < 0.10. ** p < 0.05. *** p < 0.01.

33%-67%, and 0.12 with the threshold 30%-70%), and the presence of a competitor’s hub airport negatively drive firms’ likelihood of providing the low delay service (the expected multinomial log-odds for low delay relative to high delay decrease by 0.31 with the threshold 33%-67%, and 0.35 with the threshold 30%-70%). These effects are consistent with those provided in section 3.7.1. Table 3.8 and Table 3.9 show three effects of firm characteristics on flight delay levels that are not clear in section 3.7.1: the number of flight departures positively influences the choice of the medium delay service (the expected multinomial log-odds for medium delay relative to high delay increase by 0.11 with the threshold 33%-67%, and 0.16 with the threshold 30%-70%); capacity utilization negatively drive the likelihood of providing the low delay service (the expected multinomial log-odds for low delay relative
to high delay decrease by 0.19 with both thresholds) and the medium delay service (the expected multinomial log-odds for low delay relative to high delay decrease by 0.06 with the threshold 33%-67%, and 0.07 with the threshold 30%-70%); and firms tend to provide low delay service (the expected multinomial log-odds for low delay relative to high delay increase by 0.15 with the threshold 33%-67%) or medium delay service (the expected multinomial log-odds for medium delay relative to high delay increase by 0.17 with the threshold 33%-67%) when flying to their hub airports. When a firm has many flight departures in a market, it is likely to avoid long flight delays because the long-time delay of one flight may cause delays of other flights, given the limited gate slots; however, at the same time, it is hard to keep all flights on time because of the complicated aircraft and crew scheduling issues with so many flight departures. As a result, firms are likely to provide medium level of delay as the number of flight departures increases. It is hard to manage boarding and keep flights on-time as the planes get fuller, thus firms are not likely to provide low delay (or sometimes medium delay) services as capacity utilization increases. When aircrafts are flew into the hub airports, it is likely that some other scheduled flights are awaiting for these aircrafts, thus firms have incentives to decrease delays to avoid carry over delays for other flights. When departing from the origin airport, firms are not likely to provide the low delay service (the expected multinomial log-odds for low delay relative to high delay decrease by 0.43 with the threshold 33%-67%, and 0.51 with the threshold 30%-70%), which is consistent with the results provided in section 3.7.1. In terms of competition effects, Table 3.8 and 3.9 both show that firms are likely to provide the medium delay service (the expected multinomial log-odds for medium delay relative to high delay increase by 1 with the threshold 33%-67%, and 0.75 with the threshold 30%-70%) and/or the low delay service (the expected multinomial log-odds for low delay relative to high delay increase by 0.66 with the threshold 33%-67%, and 0.71 with the threshold 30%-70%) when competitors provides high delay services, and that firms are likely to provide the low delay service when competitors provides medium delay services (the expected multinomial log-odds for low delay relative to high delay increase by 1.92 with the threshold 33%-67%, and 1.71 with the threshold 30%-70%). These results suggest that firms try to differentiate their services from competitors’, which is consistent with the insights provided in section 3.7.1 and 3.7.2. Comparing the competition effects in
Table 3.8: Parameter Estimates: Delay-33%-67% Threshold

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Delay</th>
<th>Medium Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.24</td>
<td>-0.39*</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>-0.03</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>-0.10**</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.31**</td>
<td>-0.20</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>0.01</td>
<td>0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>-0.19***</td>
<td>-0.06*</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Hub Origin</td>
<td>-0.43***</td>
<td>-0.10</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>0.15*</td>
<td>0.17**</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-Delay Probability</td>
<td>0.66*</td>
<td>1.00***</td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
<td>(0.35)</td>
</tr>
<tr>
<td>Belief of Competitors’ M-Delay Probability</td>
<td>1.92***</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.59)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-Delay Probability</td>
<td>-0.17</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>(0.32)</td>
<td>(0.33)</td>
</tr>
</tbody>
</table>

Notes: H, M and L refer to high, medium and low. Standard errors are in parenthesis.
* p < 0.10. ** p < 0.05. *** p < 0.01.

Table 3.8 and 3.9 with those in Table 3.6 and 3.7, we may see that firms are more eager to provide better services than competitors in the delay dimension than the cancellation dimension. This is consistent with the findings in section 3.7.1 that when firms react to service competition, they are likely to decrease flight delay rather than cancellation.

After analyzing how cancellation and delay decisions are driven by market characteristics, firm characteristics and competition respectively, we provide parameter estimates of the joint choice of cancellation and delay services in Table 3.10 to Table 3.11 (33%-67% threshold) and Table 3.12 to Table 3.13 (30%-70% threshold)\(^7\). Regarding market characteristics, Table 3.12 shows that number of business in the market has a marginally significant positive effect on the

\(^7\)The profits of the high cancellation and high delay service are normalized to 0 for identification.
Table 3.9: Parameter Estimates: Delay-30%-70% Threshold

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Delay</th>
<th>Medium Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.29</td>
<td>-0.09</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>0.00</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>-0.12**</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.35**</td>
<td>-0.24*</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>0.05</td>
<td>0.16***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>-0.19***</td>
<td>-0.07*</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Hub Origin</td>
<td>-0.51***</td>
<td>-0.15*</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-Delay Probability</td>
<td>0.71*</td>
<td>0.75**</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Belief of Competitors’ M-Delay Probability</td>
<td>1.70***</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td>(0.51)</td>
<td>(0.49)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-Delay Probability</td>
<td>-0.23</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td>(0.33)</td>
</tr>
</tbody>
</table>

Notes: H, M and L refer to high, medium and low. Standard errors are in parenthesis.

* $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

The likelihood of choosing low cancellation and low delay services, compared to high cancellation and high delay services (the expected multinomial log-odds for low cancellation low delay relative to high cancellation high delay increase by 0.2 with the threshold 30%-70%), which is consistent with the findings in section 3.7.1. Estimates with both cutoff thresholds (Table 3.10 to Table 3.13) suggest that as income per capita of the market increases, firms are not likely to provide medium cancellation services (i.e., medium cancellation + low delay, medium cancellation + medium delay, medium cancellation + high delay) and low delay services (low cancellation + low delay, medium cancellation + low delay, high cancellation + low delay). Specifically, one unit increase in income per capita decreases the expected multinomial log-odds for the medium cancellation low delay service relative the high cancellation high delay.
service by 0.43 with the threshold 33%-67%, and 0.39 with the threshold 30%-70%; one unit increase in income per capita decreases the expected multinomial log-odds for the medium cancellation medium delay service by 0.44 with both thresholds; one unit increase in income per capita decreases the expected multinomial log-odds for the medium cancellation high delay service by 0.42 with the threshold 33%-67%, and 0.36 with the threshold 30%-70%; one unit increase in income per capita decreases the expected multinomial log-odds for the low cancellation low delay service relative the high cancellation high delay service by 0.21 with the threshold 33%-67%, and 0.20 with the threshold 30%-70%; one unit increase in income per capita decreases the expected multinomial log-odds for the high cancellation low delay service by 0.25 with the threshold 33%-67%, and 0.29 with the threshold 30%-70%. These effects are consistent with those in Table 3.6 to Table 3.9, as well as those provided in section 3.7.1. Both Table 3.10 and Table 3.12 suggest that if there is a competitor’s hub present in the market, firms are unlikely to provide the medium cancellation and low delay service, compared to the high cancellation and high delay service (the expected multinomial log-odds for the medium cancellation low delay service relative the high cancellation high delay service decrease by 0.57 with the threshold 33%-67%, and 0.42 with the threshold 30%-70%). As discussed in section 3.7.1, the presence of a hub airport grants the competitor advantages in attracting and locking in passengers, making it difficult for the focal firm to compete. This seems to prompt the focal firm to choose not to allocate service-related resources to those markets.

In terms of firm characteristics, Table 3.10 to Table 3.13 show that as the number of flight departures increases, firms are more likely to provide medium/high cancellation and medium delay services. Specifically, one unit increase in the number of flight departures increases the expected multinomial log-odds for the medium cancellation medium delay service (relative to the high cancellation high delay service) by 0.11 with the threshold 33%-67%, and 0.20 with the threshold 30%-70%; and one unit increase in the number of flight departures increases the expected multinomial log-odds for the high cancellation medium delay service by 0.12 with the threshold 33%-67%, and 0.19 with the threshold 30%-70%. These effects reflect the results in Table 3.8 and 3.9. That is, firms are likely to provide medium delay services when they have a large number of flights serving the market. Moreover, these effects also
suggest that firms are not likely to provide low cancellation services (compared to the high
cancellation high delay service) given a large number of flight departures, which is consistent
with findings in section 3.7.1. With the threshold 33%-67% (30%-70%), one unit increase
in capacity utilization increases the expected multinomial log-odds for the low cancellation
low delay service (relative to the high cancellation high delay service) by 0.28 (0.33); it
increases the expected multinomial log-odds for the low cancellation medium delay service
by 0.48 (0.55); it increases the expected multinomial log-odds for the low cancellation high
delay service by 0.46 (0.49); it increases the expected multinomial log-odds for the medium
cancellation medium delay service by 0.19 (0.26); it increases the expected multinomial log-
ods for the medium cancellation high delay service by 0.28 (0.34); and it decreases the
expected multinomial log-odds for the high cancellation low delay service by 0.21 (0.18). To
summarize, as capacity utilization increases, firms are more likely to provide low/medium
cancellation services, because of the increased cancellation costs as planes get full, which is
consistent with findings in section 3.7.1. Consistent with results provided in Table 3.6-3.9,
Table 3.10 to Table 3.13 show that when departing from hub airports, firms are not likely to
provide medium cancellation services and/or low delay services (the expected multinomial
log-odds for the medium cancellation low delay service decreases by 0.92 with the threshold
33%-67%, and 0.83 with the threshold 30%-70%; the expected multinomial log-odds for the
medium cancellation medium delay service decreases by 0.28 with the threshold 33%-67%,
and 0.32 with the threshold 30%-70%; the expected multinomial log-odds for the medium
cancellation high delay service decreases by 0.38 with the threshold 33%-67%, and 0.26 with
the threshold 30%-70%; the expected multinomial log-odds for the low cancellation low delay
service decreases by 0.50 with the threshold 33%-67%, and 0.60 with the threshold 30%-70%;
the expected multinomial log-odds for the high cancellation low delay service decreases by
0.33 with the threshold 33%-67%, and 0.42 with the threshold 30%-70%), whereas when
flying into the hub airports, firms are not likely to provide medium/low cancellation services
(the expected multinomial log-odds for the medium cancellation low delay service decreases
by 0.56 with the threshold 33%-67%, and 0.49 with the threshold 30%-70%; the expected
multinomial log-odds for the medium cancellation medium delay service decreases by 0.36
with the threshold 33%-67%, and 0.39 with the threshold 30%-70%; the expected multinomial
log-odds for the medium cancellation high delay service decreases by 0.65 with the threshold 33%-67%, and 0.53 with the threshold 30%-70%; the expected multinomial log-odds for the low cancellation low delay service decreases by 0.28 with the threshold 33%-67%, and 0.40 with the threshold 30%-70%). These findings confirm that the complex flight scheduling issues in the hub airports make it costly to provide reliable on-time services (i.e., low delay services).

Due to the limited sample size and the large size of the service choice set, estimates for the competition effects seem to be sensitive to the specific trichotomization threshold. I therefore select to interpret only effects that are consistent with the two thresholds results. I summarize the qualitative results of the competition effects in Table 3.14 for the convenience of interpretation. In section 3.7.1, I did not find significant effects of competitors’ probability of providing high cancellation and high delay services on focal firm’s service level choices. However, with data trichotomization, I do find that competitors’ probability of providing high cancellation and high delay services has a marginally significant positive effect on the focal firm’s likelihood of providing low cancellation and high delay services, but a marginally significant negative effect on the likelihood of providing high cancellation and low delay services. It is likely that the competitors providing low quality services (high cancellation-high delay) offer poor operational management in the market due to low demand and low strategic importance of the market. It is then easy for the focal firm to attract demand, and thus provide low cancellation services in the market. However, the focal firm may not have the competitive pressure to decrease their delays given the presence of a poor quality competitor. Taking these two processes together, the focal firm is likely to provide low cancellation and high delay services, but unlikely to provide high cancellation and low delay services. If competitors are still inclined to provide high cancellation services, but their delay levels are at the medium level, the focal firm is likely to provide the low cancellation and low delay service, or the high cancellation and low delay service. These effects reflect the quality differentiation during competition in the delay dimension: the focal firm is motivated to provide low delay services when the competitors provide medium delay services, which is consistent with results presented in Table 3.8 and 3.9.

When competitors are likely to provide medium cancellation and high delay services,
Table 3.10: Parameter Estimates: Cancellation and Delay, 33%-67% Threshold, Part 1

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Cancel + Low Delay</th>
<th>Low Cancel + Medium Delay</th>
<th>Low Cancel + High Delay</th>
<th>Medium Cancel + Low Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.21</td>
<td>-0.70</td>
<td>0.19</td>
<td>2.32***</td>
</tr>
<tr>
<td></td>
<td>(0.42)</td>
<td>(0.44)</td>
<td>(0.45)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>0.02</td>
<td>-0.09</td>
<td>-0.12</td>
<td>0.02</td>
</tr>
<tr>
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<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>-0.21**</td>
<td>0.07</td>
<td>-0.11</td>
<td>-0.43***</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.11)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.33</td>
<td>0.01</td>
<td>-0.24</td>
<td>-0.57**</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
<td>(0.30)</td>
<td>(0.36)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>-0.09</td>
<td>-0.02</td>
<td>-0.09</td>
<td>0.06</td>
</tr>
<tr>
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<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.08)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>0.28***</td>
<td>0.48***</td>
<td>0.46***</td>
<td>0.00</td>
</tr>
<tr>
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<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Hub Origin</td>
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<td>-0.18</td>
<td>0.04</td>
<td>-0.92***</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.15)</td>
<td>(0.17)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>-0.28**</td>
<td>-0.15</td>
<td>-0.20</td>
<td>-0.56***</td>
</tr>
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<td>(0.14)</td>
<td>(0.15)</td>
<td>(0.16)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-H Probability</td>
<td>-0.80</td>
<td>-0.12</td>
<td>2.26*</td>
<td>-0.63</td>
</tr>
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<td>(1.11)</td>
<td>(1.19)</td>
<td>(1.16)</td>
<td>(0.83)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-M Probability</td>
<td>4.64***</td>
<td>1.95</td>
<td>-0.65</td>
<td>2.46</td>
</tr>
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<td>(1.79)</td>
<td>(1.91)</td>
<td>(2.10)</td>
<td>(1.54)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-L Probability</td>
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<td>1.32</td>
<td>-0.39</td>
</tr>
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<td>(1.31)</td>
<td>(1.46)</td>
<td>(1.10)</td>
</tr>
<tr>
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<td>(1.87)</td>
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<td>(1.41)</td>
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<td>3.06</td>
<td>2.21</td>
</tr>
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<td>(2.70)</td>
<td>(2.93)</td>
<td>(2.23)</td>
</tr>
<tr>
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<td>0.89</td>
<td>-0.40</td>
<td>-2.37**</td>
</tr>
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<td></td>
<td>(1.39)</td>
<td>(1.45)</td>
<td>(1.65)</td>
<td>(1.17)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-H Probability</td>
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<td>0.94</td>
<td>-0.41</td>
<td>2.46</td>
</tr>
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<td>(2.74)</td>
<td>(2.64)</td>
<td>(3.06)</td>
<td>(2.34)</td>
</tr>
<tr>
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<td>2.75</td>
<td>2.65</td>
<td>-3.14</td>
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<td>(2.55)</td>
<td>(2.62)</td>
<td>(3.02)</td>
<td>(2.42)</td>
</tr>
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<td>Belief of Competitors’ L-L Probability</td>
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<td>-2.34*</td>
<td>-4.22***</td>
<td>3.73***</td>
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<tr>
<td></td>
<td>(1.22)</td>
<td>(1.33)</td>
<td>(1.57)</td>
<td>(1.24)</td>
</tr>
</tbody>
</table>

Notes: H, M and L refer to high, medium and low, presented as cancellation and delay, in that order. Standard errors are in parenthesis.
* p < 0.10. ** p < 0.05. *** p < 0.01.
Table 3.11: Parameter Estimates: Cancellation and Delay, 33%-67% Threshold, Part 2

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Medium Cancel + Medium Delay</th>
<th>Medium Cancel + High Delay</th>
<th>High Cancel + Low Delay</th>
<th>High Cancel + Medium Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.48***</td>
<td>1.97***</td>
<td>0.36</td>
<td>-0.21</td>
</tr>
<tr>
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<td>(0.37)</td>
<td>(0.36)</td>
<td>(0.44)</td>
<td>(0.41)</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>-0.09</td>
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</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.08)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>-0.44***</td>
<td>-0.42***</td>
<td>-0.25***</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.21</td>
<td>-0.05</td>
<td>0.24</td>
<td>-0.36</td>
</tr>
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<td></td>
<td>(0.23)</td>
<td>(0.24)</td>
<td>(0.26)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>0.11*</td>
<td>0.04</td>
<td>-0.07**</td>
<td>0.12*</td>
</tr>
<tr>
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<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>0.19***</td>
<td>0.28***</td>
<td>-0.21***</td>
<td>-0.08</td>
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<td>(0.05)</td>
<td>(0.06)</td>
<td>(0.06)</td>
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<tr>
<td>Hub Origin</td>
<td>-0.28**</td>
<td>-0.38***</td>
<td>-0.33**</td>
<td>-0.25*</td>
</tr>
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<td>(0.12)</td>
<td>(0.14)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>-0.36***</td>
<td>-0.65***</td>
<td>0.32**</td>
<td>0.07</td>
</tr>
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<td>(0.13)</td>
<td>(0.14)</td>
<td>(0.13)</td>
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<tr>
<td>Belief of Competitors’ H-H Probability</td>
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<td>-1.79*</td>
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<td>(0.84)</td>
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<td>(0.78)</td>
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<tr>
<td>Belief of Competitors’ H-M Probability</td>
<td>1.03</td>
<td>0.96</td>
<td>3.72**</td>
<td>1.59</td>
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<td>(1.58)</td>
<td>(1.60)</td>
<td>(1.51)</td>
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<tr>
<td>Belief of Competitors’ H-L Probability</td>
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<td>1.73</td>
<td>-3.08**</td>
<td>-0.43</td>
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<td>(1.09)</td>
<td>(1.33)</td>
<td>(1.29)</td>
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<tr>
<td>Belief of Competitors’ M-H Probability</td>
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<td>-3.66**</td>
<td>0.96</td>
<td>0.91</td>
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<td>(1.46)</td>
<td>(1.55)</td>
<td>(1.54)</td>
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<td>5.27**</td>
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<td>(2.49)</td>
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<tr>
<td>Belief of Competitors’ M-L Probability</td>
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<td>-3.80***</td>
<td>-3.08**</td>
<td>-0.43</td>
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<td>(1.27)</td>
<td>(1.33)</td>
<td>(1.29)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-H Probability</td>
<td>4.22*</td>
<td>2.09</td>
<td>1.10</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td>(2.34)</td>
<td>(2.44)</td>
<td>(2.59)</td>
<td>(2.52)</td>
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<td>(2.58)</td>
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<td>(2.56)</td>
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<td>Belief of Competitors’ L-L Probability</td>
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<td>0.59</td>
<td>1.18</td>
</tr>
<tr>
<td></td>
<td>(1.27)</td>
<td>(1.32)</td>
<td>(1.34)</td>
<td>(1.25)</td>
</tr>
</tbody>
</table>

Notes: H, M and L refer to high, medium and low, presented as cancellation and delay, in that order.
Standard errors are in parenthesis.
* $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$. 
Table 3.12: Parameter Estimates: Cancellation and Delay, 30%-70% Threshold, Part 1

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Low Cancel + Low Delay</th>
<th>Low Cancel + Medium Delay</th>
<th>Low Cancel + High Delay</th>
<th>Medium Cancel + Low Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.19</td>
<td>(0.49)</td>
<td>-0.11</td>
<td>(2.35**</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>0.20*</td>
<td>(0.10)</td>
<td>0.01</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>-0.20*</td>
<td>(0.10)</td>
<td>0.05</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.36</td>
<td>(0.29)</td>
<td>0.04</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>0.04</td>
<td>(0.07)</td>
<td>-0.14</td>
<td>(0.11*</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>0.33***</td>
<td>(0.07)</td>
<td>0.55***</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Hub Origin</td>
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<td>(0.16)</td>
<td>-0.17</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Hub Destination</td>
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<td>(0.16)</td>
<td>-0.11</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-H Probability</td>
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<td>(1.39)</td>
<td>-0.23</td>
<td>(1.51)</td>
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<tr>
<td>Belief of Competitors’ H-M Probability</td>
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<td>(1.86)</td>
<td>4.84***</td>
<td>(2.31)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-L Probability</td>
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<td>(1.60)</td>
<td>-2.18</td>
<td>(1.86)</td>
</tr>
<tr>
<td>Belief of Competitors’ M-H Probability</td>
<td>4.81**</td>
<td>(2.01)</td>
<td>1.01</td>
<td>(2.42)</td>
</tr>
<tr>
<td>Belief of Competitors’ M-M Probability</td>
<td>-1.51</td>
<td>(1.87)</td>
<td>-2.77</td>
<td>(2.22)</td>
</tr>
<tr>
<td>Belief of Competitors’ M-L Probability</td>
<td>-1.92</td>
<td>(1.40)</td>
<td>2.30*</td>
<td>(1.71)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-H Probability</td>
<td>-1.72</td>
<td>(3.00)</td>
<td>2.89</td>
<td>(3.15)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-M Probability</td>
<td>1.33</td>
<td>(2.72)</td>
<td>0.99</td>
<td>(3.33)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-L Probability</td>
<td>2.84**</td>
<td>(2.72)</td>
<td>-1.54</td>
<td>(2.49)</td>
</tr>
</tbody>
</table>

Notes: H, M and L refer to high, medium and low, presented as cancellation and delay, in that order.
Standard errors are in parenthesis.
* p < 0.10. ** p < 0.05. *** p < 0.01.
Table 3.13: Parameter Estimates: Cancellation and Delay, 30%-70% Threshold, Part 2

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Medium Cancel +</th>
<th>Medium Delay +</th>
<th>High Cancel +</th>
<th>High Delay +</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.95***</td>
<td>1.85***</td>
<td>0.46</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(0.40)</td>
<td>(0.53)</td>
<td>(0.45)</td>
</tr>
<tr>
<td>Number of Businesses</td>
<td>-0.05</td>
<td>0.11</td>
<td>-0.14</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Income per Capita</td>
<td>-0.44***</td>
<td>-0.36***</td>
<td>-0.29***</td>
<td>-0.12</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
<td>(0.10)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>-0.13</td>
<td>0.11</td>
<td>0.47*</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.09)</td>
<td>(0.29)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Total Number of Flight Departures</td>
<td>0.20***</td>
<td>0.09</td>
<td>-0.04</td>
<td>0.19***</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>0.26***</td>
<td>0.34***</td>
<td>-0.18**</td>
<td>-0.09</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Hub Origin</td>
<td>-0.32***</td>
<td>-0.26**</td>
<td>-0.42***</td>
<td>-0.18</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.13)</td>
<td>(0.16)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Hub Destination</td>
<td>-0.39***</td>
<td>-0.53***</td>
<td>0.20</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.13)</td>
<td>(0.16)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-H Probability</td>
<td>0.07</td>
<td>-0.56</td>
<td>-4.29***</td>
<td>-0.10</td>
</tr>
<tr>
<td></td>
<td>(0.85)</td>
<td>(0.87)</td>
<td>(1.28)</td>
<td>(0.88)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-M Probability</td>
<td>-4.31***</td>
<td>2.28</td>
<td>5.60***</td>
<td>3.83**</td>
</tr>
<tr>
<td></td>
<td>(1.50)</td>
<td>(1.59)</td>
<td>(1.69)</td>
<td>(1.51)</td>
</tr>
<tr>
<td>Belief of Competitors’ H-L Probability</td>
<td>-2.39*</td>
<td>0.30</td>
<td>-2.25</td>
<td>-0.64</td>
</tr>
<tr>
<td></td>
<td>(1.30)</td>
<td>(1.32)</td>
<td>(1.47)</td>
<td>(1.32)</td>
</tr>
<tr>
<td>Belief of Competitors’ M-H Probability</td>
<td>-1.06</td>
<td>-3.27**</td>
<td>2.62</td>
<td>1.64</td>
</tr>
<tr>
<td></td>
<td>(1.54)</td>
<td>(1.64)</td>
<td>(1.77)</td>
<td>(1.68)</td>
</tr>
<tr>
<td>Belief of Competitors’ M-M Probability</td>
<td>-1.03</td>
<td>0.77</td>
<td>-1.55</td>
<td>-2.66</td>
</tr>
<tr>
<td></td>
<td>(1.54)</td>
<td>(1.65)</td>
<td>(1.91)</td>
<td>(1.74)</td>
</tr>
<tr>
<td>Belief of Competitors’ M-L Probability</td>
<td>-0.74</td>
<td>-2.05*</td>
<td>-1.61</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>(1.12)</td>
<td>(1.20)</td>
<td>(1.33)</td>
<td>(1.20)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-H Probability</td>
<td>6.16**</td>
<td>3.72</td>
<td>3.12</td>
<td>2.65</td>
</tr>
<tr>
<td></td>
<td>(2.40)</td>
<td>(2.56)</td>
<td>(2.82)</td>
<td>(2.73)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-M Probability</td>
<td>0.88</td>
<td>0.09</td>
<td>3.97</td>
<td>1.59</td>
</tr>
<tr>
<td></td>
<td>(2.46)</td>
<td>(2.66)</td>
<td>(2.81)</td>
<td>(2.61)</td>
</tr>
<tr>
<td>Belief of Competitors’ L-L Probability</td>
<td>1.86</td>
<td>-0.31</td>
<td>0.42</td>
<td>1.19</td>
</tr>
<tr>
<td></td>
<td>(1.41)</td>
<td>(1.55)</td>
<td>(1.63)</td>
<td>(1.45)</td>
</tr>
</tbody>
</table>

Notes: H, M and L refer to high, medium and low, presented as cancellation and delay, in that order.
Standard errors are in parenthesis.
* $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$. 
the focal firm is inclined to provide medium cancellation and low delay services, but not inclined to provide medium cancellation and high delay services. These results again reflect the quality differentiation in competition: firms would like to provide services better than competitors’ in some dimension (i.e., medium cancellation and low delay, as opposed to medium cancellation and high delay), but not exactly the same service as competitors (i.e., avoid the medium cancellation and high delay services, which are offered by the competitors). Competitors’ probability of providing medium cancellation and low delay decreases the focal firm’s probability of providing medium cancellation and high delay services. This effect suggests that when competitors are good at decreasing delay and not bad at reducing cancellation, the focal firm is not likely to match the cancellation level with the competitor but keeping a high delay level, compared to providing poor services in both dimensions (high cancellation and high delay).

The probability of competitors providing low cancellation and high delay services increases the likelihood of the focal firm providing medium cancellation and medium delay services. This result suggests some horizontal quality differentiation pattern; that is, when competitors are doing well in one dimension of the service but bad in the other, the focal firm is likely to not doing bad in both dimensions. By offering a different service package, the focal firm attracts passengers who do not like the service package provided by competitors. When competitors provide very good services (i.e., low cancellation and low delay), the focal firm is likely to provide medium cancellation and low delay services, but not likely to provide low cancellation and high delay services. This is the new insight generated by the estimation of trichotomized service quality: the high service quality of competitors does give incentives for the focal firm to improve their services to a level that is close to the competitors (i.e., medium cancellation and low delay, as opposed to low cancellation and low delay). However, firms are more likely to decrease delay than cancellation when they are not able to decrease both, which is reflected by the negative effects of competitors’ probability of providing low cancellation and low delay services on focal firm’s probability of providing low cancellation and high delay services. This is consistent with the discussions in 3.7.1 and 3.7.2: when firms are pressured by service competition, they are likely to decrease delay rather than cancellation. Overall, the estimation results with trichotomized service quality levels con-
Table 3.14: Analysis of Competition Effects

<table>
<thead>
<tr>
<th>Competitor Cancellation</th>
<th>Competitor Delay</th>
<th>Effect on Focal Firm</th>
<th>Positive</th>
<th>Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>High</td>
<td>Low C + High D</td>
<td>High C + Low D</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>Low C + Low D</td>
<td>High C + Low D</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>High</td>
<td>Medium C + Low D</td>
<td>Medium C + High D</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>Medium C + Low D</td>
<td>Medium C + High D</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>Medium C + Low D</td>
<td>Low C + High D</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>Medium D</td>
<td>Low C + High D</td>
<td></td>
</tr>
</tbody>
</table>

Notes: C and D refer to cancellation and delay.

firm the main findings in section 3.7.1; that is, firms seek to differentiate their quality from their competitors when they compete in services, and they tend to react to competition by decreasing delay. Moreover, the estimation results generate some additional insights with trichotomized flight cancellation and delay data.

3.7.3.2 Continuous Values of Service Quality-Reduced-Form Analysis

In this robustness check, I run a reduced-form analysis, keeping the original continuous (median-centered) values of the delay and cancellation rate variables. To account for the joint decisions regarding flight cancellations and delays, I run seemingly unrelated regressions using cancellation and delay as two dependent variables. As independent variables, I include all the state variables to capture market and firm characteristics. Additionally, to represent competition effects, I include competitors’ average cancellation rates and delay in minutes, and the interaction term of competitors’ cancellation and delay to capture the moderating effects of one dimension of service quality on the other dimension of service quality8.

The results are shown in Table 3.15. The effects of most market and firm characteristics are consistent with those in Table 3.3: number of business marginally decreases delay ($\beta = -4.29, p < 0.1$); income per capita increases cancellation ($\beta = 0.022, p < 0.05$); the focal firm’s cancellations ($\beta = 0.2, p < 0.01$) and delays ($\beta = 0.73, p < 0.01$) tend to be high when competitors have hub(s) in the market; cancellations tend to increase as the number

---

8I take the exponential value of the moderating variable, to keep the positive/negative signs of the main variable.
of flight departures increases ($\beta = 0.88, p < 0.01$); cancellations tend to decrease as capacity utilization increases ($\beta = -3.52, p < 0.01$); firms have more cancellations ($\beta = 0.12, p < 0.01$) and delays ($\beta = 0.82, p < 0.01$) when the origin airport is a hub.

In terms of competition effects, the main results are also consistent with previous findings. I find that the focal firm’s cancellation is influenced by competitors’ cancellation ($\beta = 0.15, p < 0.01$) but not by competitors’ delay or the interaction term of competitors’ cancellation and delay; whereas the focal firm’s delay is influenced by competitors’ delay ($\beta = 1.88, p < 0.05$), competitors’ cancellation ($\beta = 0.11, p < 0.05$), and the interaction term ($\beta = -1.74, p < 0.05$). This result shows that firms work on their delay rather than cancellation when they are threatened by competition, which is consistent with the results of the main model. I also find that the focal firm’s delay decreases as competitors’ delay decreases; however, such positive impact is weakened as the competitors’ cancellation decreases (the moderating effect is negative). This result shows that firms are more likely to decrease their delays when competitors have high service quality in only one dimension (i.e., delay or cancellation) instead of both dimensions, which is also consistent with the results from the main model. Overall, the robustness check generates results that are qualitatively consistent with those in section 3.7.1, indicating that the main conclusions are not driven by the four-level discretization of service quality choices.

### 3.8. Counterfactual Analysis: How New Entrants Drive Incumbents to Adjust Service Quality

Using the estimation results, I conduct a counterfactual analysis for the Boston-Denver market, where in the first quarter of 2010, we observe the entry of Southwest Airlines. To quantify how much the presence and choices of Southwest impact the probabilities of United providing each service level, I calculate the probabilities of United taking each service level if Southwest did not exist in the market in 2010 (given the parameter estimates) and compared them with the actual probabilities (see Table 3.16).

I observe that Southwest Airlines was initially inclined to provide low cancellation but
Table 3.15: Results of Seemingly Unrelated Regressions of Cancellation and Delay

<table>
<thead>
<tr>
<th>X Variable</th>
<th>Cancellation (%)</th>
<th>Delay (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.56***</td>
<td>-1.04***</td>
</tr>
<tr>
<td>(0.11)</td>
<td>(0.40)</td>
<td></td>
</tr>
<tr>
<td>Number of Businesses (in 1,000,000)</td>
<td>-3.50</td>
<td>-4.29*</td>
</tr>
<tr>
<td>(9.90)</td>
<td>(2.61)</td>
<td></td>
</tr>
<tr>
<td>Income per Capita (in 1,000)</td>
<td>0.022**</td>
<td>0.05</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>Competitors’ Hub</td>
<td>0.20***</td>
<td>0.73***</td>
</tr>
<tr>
<td>(0.06)</td>
<td>(0.23)</td>
<td></td>
</tr>
<tr>
<td>Total Number of Flight Departures (in 1,000)</td>
<td>0.88***</td>
<td>-0.17</td>
</tr>
<tr>
<td>(0.06)</td>
<td>(0.22)</td>
<td></td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>-3.52***</td>
<td>6.21***</td>
</tr>
<tr>
<td>(0.18)</td>
<td>(0.64)</td>
<td></td>
</tr>
<tr>
<td>Hub Origin</td>
<td>0.12***</td>
<td>0.82***</td>
</tr>
<tr>
<td>(0.04)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>Hub Destination</td>
<td>-0.01</td>
<td>-0.55***</td>
</tr>
<tr>
<td>(0.04)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>Competitors’ Cancellation</td>
<td>0.15***</td>
<td>0.11**</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(0.05)</td>
<td></td>
</tr>
<tr>
<td>Competitors’ Delay</td>
<td>0.003</td>
<td>1.88**</td>
</tr>
<tr>
<td>(0.004)</td>
<td>(0.91)</td>
<td></td>
</tr>
<tr>
<td>Competitors’ Cancellation*Competitors’ Delay</td>
<td>1.14</td>
<td>NA</td>
</tr>
<tr>
<td>(1.51)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competitors’ Delay*Competitors’ Cancellation</td>
<td>NA</td>
<td>-1.74**</td>
</tr>
<tr>
<td>(0.88)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Standard errors are in parenthesis.
* p < 0.10. ** p < 0.05. *** p < 0.01.

...high delay services, with its probability of offering low cancellation and high delay services being 50% on average. In response, United became more likely to provide higher service quality: the probability of providing both low cancellation and low delay services increased by approximately 15%-60%, while its probabilities of providing the lowest level of service quality with high cancellation and high delay dropped by approximately 37%. Overall, I find evidence that United significantly improved its service quality with the presence of Southwest in the market.

I conduct similar counterfactual analyses for the market Denver-Minneapolis, where there were two new entrants. The United Airlines served in this market as a monopoly firm before 2009. In the second quarter of 2009, the Southwest Airlines entered the market and I observe...
Table 3.16: Reaction of UA to Entry of Southwest

<table>
<thead>
<tr>
<th>Time</th>
<th>Predicted L-L Prob of UA (no Southwest)</th>
<th>Actual L-L Prob of UA (Southwest)</th>
<th>L-L Prob of Southwest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1-2010</td>
<td>0.1968</td>
<td>0.3189</td>
<td>0.2728</td>
</tr>
<tr>
<td>Q2-2010</td>
<td>0.1999</td>
<td>0.3125</td>
<td>0.2962</td>
</tr>
<tr>
<td>Q3-2010</td>
<td>0.1788</td>
<td>0.2989</td>
<td>0.2593</td>
</tr>
<tr>
<td>Q4-2010</td>
<td>0.2024</td>
<td>0.3274</td>
<td>0.2842</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time</th>
<th>Predicted H-L Prob of UA (no Southwest)</th>
<th>Actual H-L Prob of UA (Southwest)</th>
<th>H-L Prob of Southwest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1-2010</td>
<td>0.1954</td>
<td>0.3278</td>
<td>0.0685</td>
</tr>
<tr>
<td>Q2-2010</td>
<td>0.1572</td>
<td>0.2456</td>
<td>0.1003</td>
</tr>
<tr>
<td>Q3-2010</td>
<td>0.1857</td>
<td>0.3218</td>
<td>0.0680</td>
</tr>
<tr>
<td>Q4-2010</td>
<td>0.1805</td>
<td>0.3000</td>
<td>0.0636</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time</th>
<th>Predicted L-H Prob of UA (no Southwest)</th>
<th>Actual L-H Prob of UA (Southwest)</th>
<th>L-H Prob of Southwest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1-2010</td>
<td>0.2212</td>
<td>0.1275</td>
<td>0.5610</td>
</tr>
<tr>
<td>Q2-2010</td>
<td>0.2266</td>
<td>0.1421</td>
<td>0.4468</td>
</tr>
<tr>
<td>Q3-2010</td>
<td>0.2079</td>
<td>0.1248</td>
<td>0.5607</td>
</tr>
<tr>
<td>Q4-2010</td>
<td>0.2127</td>
<td>0.1238</td>
<td>0.5442</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time</th>
<th>Predicted H-H Prob of UA (no Southwest)</th>
<th>Actual H-H Prob of UA (Southwest)</th>
<th>H-H Prob of Southwest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1-2010</td>
<td>0.3866</td>
<td>0.2259</td>
<td>0.0977</td>
</tr>
<tr>
<td>Q2-2010</td>
<td>0.4164</td>
<td>0.2998</td>
<td>0.1566</td>
</tr>
<tr>
<td>Q3-2010</td>
<td>0.4276</td>
<td>0.2545</td>
<td>0.1120</td>
</tr>
<tr>
<td>Q4-2010</td>
<td>0.4045</td>
<td>0.2488</td>
<td>0.1080</td>
</tr>
</tbody>
</table>

Notes: H and L refer to high and low, presented as cancellation and delay, in that order. With the presence of Southwest, United Airlines are more likely to provide better on-time performances (decreased delays).

United improved service quality, a response similar to that in the market Boston-Denver (i.e., the probability of providing the low cancellation, low delay service increased by 18.6% on average, and the probability of providing the high cancellation, low delay service increased by 34.1%) (see Table 3.17). In the first quarter of 2010, Delta Airlines also entered this market. Comparing this actual scenario with the counterfactual situation where Delta is not present, we find that United Airlines and Southwest Airlines decreased their delays as response. However, the change in probabilities of choosing a better service quality are significantly smaller (less than 10%) than the changes estimated when Southwest entered. In fact, Southwest Airlines also responded to the entry of Delta by increasing its probability
of providing a better service, which, given my results, decreased the motivation of United Airlines to improve its service quality.

3.9. Discussion and Conclusion

I study how various market characteristics, firm characteristics, and competition factors drive firms’ service performance at the market level. To capture firm service performance at the market level, I use unique combinations of flight cancellation levels and flight delay levels. I use a static game estimation for my analysis, and conduct robustness checks by static game estimations with different discretization criteria, as well as some reduced-form analysis. In addition, I show counterfactual analyses on the market entry effects in two representative markets.

This section is organized as follows: in section 3.9.1 I summarize the key findings of this paper; in section 3.9.2 I outline the contributions of this paper to the literature; in section 3.9.3 I seek to provide detailed managerial implications with the findings, specifically, I quantify the change of competitors’ service quality decisions on the shift of the focal firm’s profits; in section 3.9.4 I briefly discuss the research implications for policy makers, the research limitations of this study, and provide directions to future research.

3.9.1 Summary of Key Findings

I find that market characteristics, firm characteristics, and competition have different levels of influence on flight cancellation and flight delay decisions, and they also drive cancellation and delay decisions in an asymmetric manner. Market characteristics have some weak effects on firms’ probability of providing very good services (i.e., low cancellation and low delay). Specifically, the size of potential business customers (number of businesses) in the market weakly increases firms’ tendency to provide very good services, while the presence of a competitors’ hub airport decreases their tendency to offer good services. Firm characteristics have strong impact on flight cancellation decisions: the number of flight departures and the presence of a hub airport in the market are likely to increase flight cancellation, while capacity utilization reduces firms’ incentives to cancel flights. In service competition, firms
Table 3.17: Reaction of Incumbents to New Entrants: Denver-Minneapolis

<table>
<thead>
<tr>
<th>Time</th>
<th>Predicted L-L Prob</th>
<th>Actual L-L Prob</th>
<th>Predicted H-L Prob</th>
<th>Actual H-L Prob</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UA</td>
<td>WN</td>
<td>DL</td>
<td>UA</td>
</tr>
<tr>
<td>Q2-2009</td>
<td>0.2018</td>
<td>NA</td>
<td>NA</td>
<td>0.1974</td>
</tr>
<tr>
<td>Q3-2009</td>
<td>0.1363</td>
<td>NA</td>
<td>NA</td>
<td>0.1702</td>
</tr>
<tr>
<td>Q4-2009</td>
<td>0.2012</td>
<td>NA</td>
<td>NA</td>
<td>0.2486</td>
</tr>
<tr>
<td>Q1-2010</td>
<td>0.1049</td>
<td>0.2310</td>
<td>NA</td>
<td>0.1104</td>
</tr>
<tr>
<td>Q2-2010</td>
<td>0.1045</td>
<td>0.2471</td>
<td>NA</td>
<td>0.1109</td>
</tr>
<tr>
<td>Q3-2010</td>
<td>0.0947</td>
<td>0.2309</td>
<td>NA</td>
<td>0.0974</td>
</tr>
<tr>
<td>Q4-2010</td>
<td>0.1086</td>
<td>0.2522</td>
<td>NA</td>
<td>0.1120</td>
</tr>
</tbody>
</table>

<table>
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<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UA</td>
<td>WN</td>
<td>DL</td>
<td>UA</td>
</tr>
<tr>
<td>Q2-2009</td>
<td>0.1589</td>
<td>NA</td>
<td>NA</td>
<td>0.0577</td>
</tr>
<tr>
<td>Q3-2009</td>
<td>0.0817</td>
<td>NA</td>
<td>NA</td>
<td>0.0532</td>
</tr>
<tr>
<td>Q4-2009</td>
<td>0.1468</td>
<td>NA</td>
<td>NA</td>
<td>0.0946</td>
</tr>
<tr>
<td>Q1-2010</td>
<td>0.2131</td>
<td>0.5180</td>
<td>NA</td>
<td>0.2134</td>
</tr>
<tr>
<td>Q2-2010</td>
<td>0.1844</td>
<td>0.4816</td>
<td>NA</td>
<td>0.2142</td>
</tr>
<tr>
<td>Q3-2010</td>
<td>0.1774</td>
<td>0.4775</td>
<td>NA</td>
<td>0.1918</td>
</tr>
<tr>
<td>Q4-2010</td>
<td>0.1796</td>
<td>0.3419</td>
<td>NA</td>
<td>0.2029</td>
</tr>
</tbody>
</table>

Notes: H and L refer to high and low, presented as cancellation and delay, in that order.
After the entry of Southwest, United Airlines are more likely to provide better on-time performances (decreased delays). After the entry of Delta, United and Southwest are more likely to provide on-time performances, but the change in probabilities of choosing a better service quality are significantly smaller than the changes when Southwest entered.
show strong tendency to differentiate their services from those offered by their competitors. Moreover, firms are likely to have both horizontal differentiation and vertical differentiation in services. For example, they tend to avoid providing exactly the same combination of flight cancellation level and flight delay level as their competitors, to horizontally differentiate their services from those of their competitors. Vertical differentiation is found in flight delay decisions. When competitors have medium (high) level of flight delay, firms are inclined to have low (medium) level of flight delay. Overall, it seems that flight cancellation decisions tend to be strongly driven by firm characteristics related to cancellation costs and rescheduling convenience, while flight delay decisions are strongly responsive to competition and firms tend to adjust their flight delay levels to differentiate their services from those of their competitors. In the counterfactual analysis, I show that a market entry indeed motivates incumbent firms motivated to improve their services; however, the extent of service improvement of the incumbent firm also depends on the specific service levels of the new entrant and other incumbent firms.

3.9.2 Contribution to the Literature

This study mainly contributes to the service marketing literature. Previous service marketing literature (e.g., Lariviere, 2008; Spreng and Mackoy, 1996; Zeithaml et al., 1996) establishes the importance of service quality on firms’ market success. But we observe that not every firm provides good services, and the same firm seems to offer different levels of services in different markets. This seems to be inconsistent with findings in the service marketing literature, because all firms should provide good services if services are the key for firms’ success. This study is motivated by the complicated variations in service quality (measured by flight cancellation and flight delay) across firms and markets. I come up with a model to explain the service quality variation, and explicitly account for service competition. Most service marketing papers focus on discussing the outcomes (e.g., customer retention, market share) of improved service quality, except for a few studies discussing how firms may improve service quality by being market oriented (Raju and Lonial, 2001), formalizing the selling process, and/or applying a cross-functional team structure (Froehle et al., 2000), but none of these studies account for competition. To my best knowledge, this is the first paper that
introduces static game estimation (that accounts for endogenous competition effects) to the service marketing literature, to explain firms’ service quality decisions.

The findings also enrich the service marketing literature. First, I find that flight cancellation and flight delay are asymmetrically influenced by firm characteristics and competition. This finding highlights the importance of treating service quality as a multi-dimensional concept, regardless of studying the antecedents or consequences of service quality. Second, I find strong evidence of service quality differentiation, both horizontally and vertically, in the context of competition. This finding suggests that it is not always optimal for firms to improve their services, indeed, it is beneficial to improve services when there is room for firms to horizontally differentiate themselves from competitors (i.e., have different service competitive advantages from competitors’), and/or vertically differentiate themselves from competitors (i.e., it is possible to provide better services than competitors).

3.9.3 Managerial Implication: Competitors’ Service Quality Adjustments on the Focal Firm’s Profits

This research offers some managerial implications related to when it is profitable for firms to improve their service quality and how they should react to competitive moves by adjusting their own service quality. Specifically, firms should invest service-related resources in markets where the demand from business customers is strong, and/or there is room to differentiate their services from competitors’. Moreover, if firms intend to decrease flight cancellations, efficient capacity management is critical; if firms are threatened by competitors’ service quality actions, decreasing delays is profitable. These are the key managerial implications of this paper.

In this section, I take an in-depth look at how competitors’ service quality adjustments influence the profitability of the focal firm when it provides each service quality level. I therefore conducted two counterfactual analyses. In the two scenarios, the market consists of a focal firm and a competitor, and the competitor initially has a 25% chance to provide each level of service quality. Then the competitor improves its level of delay (Scenario 1) or its level of cancellation (Scenario 2), so it has a 50% chance to provide low delay and
high cancellation (Scenario 1) or high delay and low cancellation (Scenario 2), a 50% chance
to provide low delay and low cancellation (Scenario 1) or low delay and low cancellation
(Scenario 2), and no chance of providing the other two levels of service. I compare the profit
change (in percentage) of the focal firm when it provides each level of service quality (profits
from high delay and high cancellation are always 0).

I am aware that other state variables also influence the focal firm’s profits, so I also
include two subcases in each scenario. First, I assume the focal firm has a high level of flight
departures and a high level of capacity utilization, and it operates between two hub airports
(denoted as “strong”). Second, I assume the focal firm has a low level of flight departures
and a low level of capacity utilization, and it does not operate between any hub airports
(“weak”). In both subcases, I assume the focal market does not contain many businesses and
experiences low state income per capita; the competitor also does not have a hub airport in
the market.

In Table 3.18, I provide the focal firm’s profit percentage shifts, corresponding to the
competitors’ service quality adjustments. The focal firm’s profits from reducing cancellation
or delay decrease substantially if the competitor reduces its level of delay. This result emerges
because the competitor is likely to provide low delay and low cancellation service (50% of
chance), and the focal firm has a strong aversion to competing intensively with the competitor
by improving its service quality in this case. Moreover, the focal firm’s profits from providing
low delay services decrease more if the focal firm is strong, rather than weak. It is more
costly for the focal firm to provide good service quality if it supplies large quantities of flights
or has a hub in the market. The negative effects of the other state variables all contribute
to profit decreases when the focal firm is strong.

If, however, the competitor reduces its level of cancellation, the focal firm’s profits from
providing low delay services may increase. The profit increase is mainly caused by the good
likelihood that the competitor will provide high delay and low cancellation service (50% of
chance), which substantively increases the focal firm’s profits through reduced delay.
The focal firm may even differentiate itself from its competitor by improving its on-time
performance.

Note that I don’t account for competitor’s strategic reaction in Table 3.18, to show the
Table 3.18: Focal Firm’s Profits and Competitors’ Service Quality Adjustment

<table>
<thead>
<tr>
<th>Focal Firm</th>
<th>Change in Profit of L-L Strategy</th>
<th>Change in Profit of H-L Strategy</th>
<th>Change in Profit of L-H Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong</td>
<td>-149.68%</td>
<td>-1191%</td>
<td>-84.70%</td>
</tr>
<tr>
<td>Weak</td>
<td>-109.54%</td>
<td>-126.73%</td>
<td>-403.93%</td>
</tr>
</tbody>
</table>

Table 3.19: Focal Firm’s Profits and Competitors’ Service Quality Adjustment (converged results)

<table>
<thead>
<tr>
<th>Focal Firm</th>
<th>Change in Profit of L-L Strategy</th>
<th>Change in Profit of H-L Strategy</th>
<th>Change in Profit of L-H Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong</td>
<td>-16.47%</td>
<td>-2.22%</td>
<td>-77.78%</td>
</tr>
<tr>
<td>Weak</td>
<td>-10.80%</td>
<td>-3.57%</td>
<td>-63.83</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Focal Firm</th>
<th>Change in Profit of L-L Strategy</th>
<th>Change in Profit of H-L Strategy</th>
<th>Change in Profit of L-H Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong</td>
<td>+14.71%</td>
<td>+17.33%</td>
<td>-48.33%</td>
</tr>
<tr>
<td>Weak</td>
<td>+55.60%</td>
<td>+57.17%</td>
<td>-104.76%</td>
</tr>
</tbody>
</table>

Note: H and L refer to high and low, presented as cancellation and delay, in that order.

direct effects of competitor’s service quality changes on focal firm’s profits of choosing each service quality. I show the converged results (accounting for competitive reactions between the focal firm and the competitor) in Table 3.19. I see that signs of profit changes are consistent in these two tables, but most of the differences are smaller in the converged setting, because the competitor’s reaction makes its choice probabilities more evenly distributed than those in the initial setting, and the evenly distributed choice probabilities reduce the focal firm’s profit differences across scenarios.
3.9.4 Research Implications and Future Research

In addition to the managerial implications discussed in section 3.9.3, the results also lead to recommendations for policy makers regarding effective ways to increase overall service quality in the industry (e.g., Tarmac Delay Rules implemented in 2010). This research suggests some potential regulations to improve airlines’ service quality: discourage firms from over-supplying flights and/or expanding their hub cities; encourage the market entry of firms providing good services in one dimension instead of superior services in both dimensions.

This paper enriches the services marketing literature by investigating factors that drive firms’ service quality decisions along different dimensions of services. There are three limitations of this research. First, because of the data limitation, I use flight cancellation and flight delay to represent service quality in the airline industry. I am aware that these two constructs may not be sufficient to capture the entire concept of service quality in this industry, such as flight attendant courtesy, availability of food and drink, etc.. Second, service quality discretization may wash out some data variation, though the robustness checks show that the key qualitative insights generated by the estimation are not subject to the data discretization. Finally, the service quality of a firm might carry-over as time goes by, but we do not account for it in this paper.

Future studies may seek to address the limitations listed above. Moreover, additional studies can extend this research problem to other industries, such as hotels and tourism services. It also would be interesting to incorporate firms’ service recovery decisions into the framework, to test whether service recovery decisions are influenced by the same set of factors as service delivery decisions.
Chapter 4

Conclusions

In this dissertation, I focus on understanding how firms make service quality decisions. In particular, in essay I, I study how firms’ service quality decisions are influenced by the pricing decisions and performance outcomes in the presence of competition. In essay II, I consider the quality of two service dimensions, and explore how the focal firm’s service quality decisions (regarding to both service dimensions) are influenced by market and firm characteristics, and competitors’ service quality decisions. Both essays find that service quality decisions are potentially influenced by many factors such as prices, capacity management, demand, and competitors’ service performances. Therefore, it is not always feasible or optimal for firms to improve their service levels.

My dissertation brings novel perspectives, in terms of data, methodology, and substantive insights, to the services marketing literature. Whereas most existing literature largely relies on survey data (e.g., Lariviere, 2008; Zeithaml et al., 1996), I use secondary data on service quality (i.e., flight delays and/or flight cancellations) and other relevant variables (e.g., price, demand, capacity) collected by Bureau of Transportation Statistics (BTS) in my dissertation. There are a few advantages of secondary data compared to survey data. First, the secondary data are collected monthly/quarterly since year 1993. They allow me to explore the dynamic evolution of service quality levels and other decision or outcome variables of most major firms (e.g., United Airlines, Delta Airlines). In my essay I, I come up with a structural vector autoregressive panel model to assess how service quality, price, and outcome variables drive each other dynamically, which is impossible to do with cross-sectional or two-wave survey data. Second, because of the panel data structure, I am able to control for firm-specific and/or market-specific fixed effects in the estimations to reduce potential bias in coefficients I am interested in. It is also nearly impossible to include so many fixed effects with cross-sectional or two-wave survey data. Third, most of existing literature used subjective measurements for service quality, which are influenced by the perception of each individual
customer. However, firms usually cannot control customer perception; instead, it is feasible for firms to work on objective dimensions of service quality, such as on-time performance, facility availability, and service failure minimization. By using objective measurements for service quality, my dissertation may generate actionable implications for firms.

My dissertation also introduces cutting-edge methodologies to services research. In essay I, I propose a structural vector autoregressive panel model that features (1) a three-way data structure with variables varying across firms, markets, and time; (2) a vast number of markets (582 routes) and firms (seven airlines), such that the cross-sections of the data exceed the time dimensions (maximum 72 quarters); (3) dependence among markets, mainly caused by reciprocal routes; and (4) missing price information (11.41% of observations on price). To estimate the proposed structural vector autoregressive panel model, I impute the missing price values using missing at random specification (e.g., Little and Rubin, 1987), correct for cross-sectional dependence between each pair of reciprocal markets (Mutl, 2009), and modify the three-step estimation procedure suggested by Holtz-Eakin et al. (1987) to account for the unbalanced panel structure in the data. To my best knowledge, my essay I is the first study using the panel vector autoregressive model to study the evolution of service quality levels. Furthermore, I also modify the conventional Panel vector autoregressive model to account for special features in the data (i.e., unbalanced panel structure, market dependence, missing value). In essay II, I use the static game estimation method to account for the simultaneous service quality decisions among competing firms in each market; i.e., the focal firm may anticipate the service quality decisions of competing firms and determines its service quality level accordingly. Static game estimation recently emerged in the structural econometrics field. To my best knowledge, my essay II is the first paper bringing this estimation method to services marketing literature. In summary, I believe my two essays introduce new estimation methods to services marketing literature, and therefore provide methodological references for future research in this domain.

My dissertation also provides substantive insights to the services marketing literature and practices. While most previous literature discusses the potential positive outcomes of improving service quality (e.g., Grewal et al., 2010; Rust et al., 2002), or what organizational structures may improve service quality (e.g., Froysh et al., 2000; Raju and Lonial, 2001),
in my dissertation, I explore how service quality decisions of firms are influenced by other factors, which is a research problem not studied in previous literature. Findings of my dissertation suggest that it is not always feasible/optimal for firms to improve their service quality, and service quality decisions are influenced by factors such as prices, capacity management, demand, and competitors’ service performances. These findings provide explanations for why many firms do not provide good services, or not keep improving service quality. Indeed, it is costly to provide good services, thus firms should improve their services when they are able to achieve efficient management and increased revenue, which depend not only on service quality but also on other decisions, such as the pricing decision. These insights are consistent with those from the service profit chain literature (e.g., Heskett, Jones, man, Sasser and Schlesinger, 1994; Raju and Lonial, 2001; Kamakura, Mittal, de Rosa and Mazzon, 2002). Furthermore, firms do not operate independently in each market; instead, they are constantly influenced by their competitors. The focal firm’s service quality may be perceived differently by customers as competitors’ service quality levels vary. Firms may have incentives to offer better services than competitors, but at the same time they need to consider the cost of providing better services than competitors. Taking the competition pressure and cost concerns together, firms are likely to provide better services than their competitors when competitors do not provide good services, because there is room for focal firms to improve services but not at high costs. In sum, firms do have the tendency to vertically differentiate their service quality from competitors (Moorthy, 1988), conditional on that competitors are not strong in services. In addition, given that services often include more than one dimension, firms are also inclined to differentiate horizontally. That is, firms tend to offer good quality in service dimensions where competitors are weak. The insights of vertical and horizontal service quality differentiation are consistent with those in competition literature (e.g., de Palma, V., Papageorgiou and Thisse, 1985; Moorthy, 1988; Tirole, 1989; Wauthy, 1996). Findings of my dissertation add novel insights to the services marketing literature, by bringing the concerns of profitability, feasibility, and competition into the discussion of service quality decisions. Moreover, these insights may serve as references for service-based firms in making service quality decisions.

In summary, my dissertation explores research problems that have not been studied
in extant service marketing literature, and it brings novel perspectives in terms of data, methodology and insights. I hope my dissertation will provoke more future research in relevant problems.
Bibliography


Iyer, G. and Seetharaman, P. B. (2005), Quality and location in retail gasoline markets.


Mutl, J. (2009), Panel var models with spatial dependence.


Snider, C. (2009), Predatory incentives and predation policy: The american airlines case.


Appendix

Supplementary documents

In this Appendix we present descriptive figures to show patterns of our four key variables in our data. These variables are: service quality, price, capacity utilization, and number of passengers served. We also present the impulse response functions for capacity utilization and number of passengers served.
Figure A.1: Time Variation in Logit Delay for Select Routes
Figure A.2: Time Variation in Log Price for Select Routes
Figure A.3: Time Variation in Log Number of Passengers Served for Select Routes
Figure A.4: Time Variation in Logit Capacity Utilization for Select Routes
Figure A.5: Impact on Capacity Utilization: Impulse Response Functions
Figure A.6: Impact on Number of Passenger Served: Impulse Response Functions
VITA

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Research Interests
Substantive Area: Service Quality Competition, Salesforce Compensation, Firm Alliance.
Methodology: Empirical Industrial Organization, Multivariate Panel Data Analysis, Econometrics.

Working Papers

Publications