ABSTRACT

Title of Document: UNDERSTANDING CUSTOMER CHOICES IN SERVICE OUTSOURCING AND REVENUE MANAGEMENT

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This dissertation investigates customer behavior modeling in service outsourcing and revenue management in the service sector (i.e., airline and hotel industries). In particular, it focuses on a common theme of improving firms' strategic decisions through the understanding of customer preferences.

Decisions concerning degrees of outsourcing, such as firms' capacity choices, are important to performance outcomes. These choices are especially important in high-customer-contact services (e.g., airline industry) because of the characteristics of services: simultaneity of consumption and production, and intangibility and perishability of the offering. Essay 1 estimates how outsourcing affects customer choices and market share in the airline industry, and consequently the revenue implications from outsourcing. However, outsourcing decisions are typically endogenous. A firm may choose whether to outsource or not based on what a firm expects to be the best outcome. Essay 2 contributes to the literature by proposing a

structural model which could capture a firm's profit-maximizing decision-making behavior in a market. This makes possible the prediction of consequences (i.e., performance outcomes) of future strategic moves.

Another emerging area in service operations management is revenue management. Choice-based revenue systems incorporate discrete choice models into traditional revenue management algorithms. To successfully implement a choice-based revenue system, it is necessary to estimate customer preferences as a valid input to optimization algorithms. The third essay investigates how to estimate customer preferences when part of the market is consistently unobserved. This issue is especially prominent in choice-based revenue management systems. Normally a firm only has its own observed purchases, while those customers who purchase from competitors or do not make purchases are unobserved. Most current estimation procedures depend on unrealistic assumptions about customer arriving. This study proposes a new estimation methodology, which does not require any prior knowledge about the customer arrival process and allows for arbitrary demand distributions. Compared with previous methods, this model performs superior when the true demand is highly variable.

UNDERSTANDING CUSTOMER CHOICES IN SERVICE OUTSOURCING AND REVENUE MANAGEMENT

By

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Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Doctor of Philosophy 2016

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Acknowledgements

First, I would like to thank my advisor Martin Dresner. Without you it would not be possible for me to complete my dissertation. You have been such an amazing mentor for me. Thank you for your great guidance, support and trust; thank you for not giving me up all the time. It is invaluable to me. I cannot thank you enough from the bottom of my heart.

I would also like to thank my committee members. Thank you Professor Curt Grimm, for your constant encouragement and kind help ever since I joined the program. I am so grateful. Thank you Professor Philip Evers, Professor Zhi-Long Chen, and Professor Ali Haghani. Thank you for serving as my committee members, thank you for your valuable comments and suggestions, both on my dissertation and on my life.

I also thank Professor Robert Windle, Professor Yue Maggie Zhou and Professor Christian Hofer, for your kind help and valuable suggestions on my research over the past years. I also thank the professors and colleagues from the Department of Logistics, Business, and Public Policy.

Finally I would like to thank my wife and parents. Thank you for all your love, sacrifices, and for being around.

Thank you all.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Overview

This dissertation investigates customer behavior modeling in service design and revenue management in the service sector (i.e., airline and hotel industries). In particular, it focuses on a common theme of improving firms' strategic decisions through the understanding of customer preferences.

In recent years, services operations management has become an active area. The most important and distinguishing features of services are customer contact, intangibility and simultaneity of production and consumption (Chase and Apte, 2007; Roth and Menor, 2003). In service operations management research and practice, a common question is how to help firms deploy their operations to deliver services effectively to target customers at the right time (Roth and Menor, 2003). To answer this question, it requires to examine customers' incentives and decision processes (e.g., what to buy, how much to pay, when to buy, and etc.) and include those into firms' decision-making (Shen and Su, 2007). However, traditional operations management often focuses on the manufacturing, but not customers. This dissertation studies how to understand customer choice behavior and include that into firms' decision-making.

Decisions concerning degrees of outsourcing (e.g. which service provider to outsource, and how much to outsource), as firms' capacity choices, are important service structural designs. These choices are especially important in high-customer-contact services (e.g., airline industry) because of the characteristics of services:

simultaneity of consumption and production, and intangibility and perishability of the offering (Roth and Menor, 2003). Therefore, it is meaningful for a firm to assess the consequence of outsourcing before making such a strategic move. Theoretical work has predicted that outsourcing can have a direct impact on firms' performance (see, e.g., Williamson, 1975, 1985; Grossman and Hart, 1986; Hart and Moore, 1990). However, there exists no clear empirical evidence in the literature (Lafontaine and Slade, 2007). Previous research either has no clear answers about the impact of outsourcing on firms' overall performance (e.g., market share and profit) (Kosová et al., 2012), or only has findings of outsourcing on firms' operational performance (e.g., service quality) (Forbes and Lederman, 2010; Novak and Stern, 2008). In this dissertation, Essay 1 fills the gap by investigating how outsourcing affects customer choices and market share in the airline industry, and consequently, revenue implications.

In addition, outsourcing decisions are typically endogenous. A firm may choose whether to outsource or not based on what a firm expects would give the best outcomes. Such optimizing behavior raises endogeneity concerns when assessing the effect of outsourcing on firms' performance (Masten, 1993). In addition, previous research in this area all use reduced-form models. Lucas (1976) argues that it is naïve to predict the outcomes of future firms' policy changes based on only historical data, without considering possible firms' behavior changes over time. There is a call for structural models to empirically evaluate outsourcing outcomes in the literature (Lafontaine and Slade, 2007). Essay 2 contributes to the literature by proposing a structural model to jointly estimate demand and supply sides, which could capture a firm's profit-maximizing behavior. It makes possible the prediction of consequences of future strategic moves.

Another emerging area in service operations management is revenue management. Originated from the kind of inventory management problems (Belobaba 1989), revenue management has been moving from product-based revenue management to choice-based revenue management (Vulcano et al., 2010; Shen and Su, 2007). Choice-based revenue system incorporates discrete choice models into traditional revenue management algorithms. It helps to understand customer behavior and customize products accordingly to improve a firms' revenue. In addition, empirical research confirm that transforming from traditional revenue management to choice-based revenue management systems could increase 1~5% a firm's revenue (Vulcano et al., 2010). To successfully implement any choice-based revenue systems, it is necessary to estimate customer preferences as a valid input to optimization algorithms. However, most current estimation procedures in existing literature depend on unrealistic assumptions about customer arriving, such as Poisson distribution (Newman et al., 2014; Vulcano et al., 2010) to keep the model tractable. However, most real data in revenue management systems have much higher variabilities than commonly assumed Poisson distribution in existing literature. In this dissertation, Essay 3 proposes a new estimation methodology with no requirement of demand distribution assumptions.

1.2 Summary of Results

1.2.1 The Impact of Outsourcing Regional Flights on Network Airlines' Demand

The first essay examines firms' service outsourcing and its impact on customer choices by using data from the airline industry. In the U.S. airline industry, regional airlines provide "feeder service" on some short and low density routes under contracts with network airlines. In addition, network airlines may use their owned regionals and/or independent regional airlines. However, there is scarce empirical research on how outsourcing regional flights affect network airlines' demand side. This study is the first attempt to quantify the impact of outsourcing regional flights on the network airlines' market share. In general, our results suggest that passengers prefer network airlines' owned regional flights over independent regional flights, even after controlling for firm-level factors. It indicates that vertical integration incurs higher market share than outsourcing. Our scenario analysis confirms that using our parsimonious model, network airlines' managers could quantify the marginal effect of operating vertical integrated and independent regional airlines on the market demand. Based on certain assumptions, our model could help executive managers to assess the consequence of outsourcing regional flights. More importantly, our findings are meaningful since there is no clear empirical evidence on how outsourcing affects firms' performance in the literature (Lafontaine and Slade, 2007).

1.2.2 Assessing the Consequences of Outsourcing: Structural Estimation from the U.S. Airline Industry

In Essay 1, we aim to examine the consequences of outsourcing on a firm's demand. However, there are still some questions unanswered. For example, what is the impact of outsourcing on price and profit? In Essay 2, using data in the U.S. airline industry, we extend the model in the following two ways. First, we allow customers to have different tastes in product characteristics. For example, in practice, leisure passengers may have higher price sensitivity, while business passengers may put more attention to flight flexibility and service quality. Secondly, we propose a structural model to jointly estimate demand and supply. On the supply side, a game theoretic model is employed to capture market structure and strategic interactions between firms. This approach could reveal a firm's profit-maximizing behavior during its decision making and makes possible the prediction of consequences of future strategic moves based on historical data.

1.2.3 Estimating Customer Preferences with Censored Sales Data in Revenue Management

The third essay investigates how to estimate customer preferences when part of the market is consistently unobserved. This issue is especially prominent in choice-based revenue management systems, since estimates of customer preferences are required as inputs for revenue management algorithms. This is challenging because normally a firm only has its own observed purchases, while those customers who purchase from competitors or do not make purchases are unobserved. Therefore, directly applying most traditional methods in statistics to this discrete choice problem with missing data could incur biased estimation. Some existing methods depend on restrictive assumptions of demand distributions, e.g., Poisson distribution. However, there are two main drawbacks for this group of methods: (1) widely adopted Poisson demand distribution has a much lower variability than those in real revenue management data; and (2) more importantly, since a significant part of the market is consistently unobserved, assumptions on market demand are unlikely to be either accurate or verified. In this study, simulation tests, based on real industrial data from a hotel chain, demonstrate that an inaccurate specification of demand distributions could easily cause over 16% estimation error. It is prominent since previous empirical research has reported that estimation error of over 10% could totally deteriorate the benefit of implementing choice-based revenue management systems (Vulcano et al., 2010). This study proposes a new estimation methodology based on case-control sampling with adjustment of missing data. It does not require any prior knowledge about the customer arrival process and allows for arbitrary demand distributions. Therefore, this estimation procedure can be implemented in many realistic industry cases. Compared with previous methods, this model performs superior when the true demand is highly variable and is far different from the assumed Poisson distribution.

1.3 Outline

The rest of this dissertation is organized as follows. Three Essays are presented in the following chapters respectively. The last chapter concludes this dissertation and provides some future research directions.

Chapter 2: The Impact of Outsourcing Regional Flights on Network Airlines' Demand

2.1 Introduction

Over the past two decades, U.S. network airlines (e.g., American Airlines, United Airlines and etc.) have had to fight with the increasing encroachment of low-cost carriers (e.g., Southwest Airlines, JetBlue and etc.) into their markets[1]. As a result, the share of the U.S. domestic passenger market served by network carriers has significantly diminished from 69.4% (219 million passengers) in 1998 to 55.8% (182 million passengers) in 2009.[2] During these harsh times, we have observed considerable consolidation happening among network carriers over the past 10 years, such as mergers between Delta Airlines and Northwest Airlines, and between United Airlines and Continental Airlines, and more recently between American Airlines and US Airways in 2014 after American Airlines stepped out of bankruptcy. As a consequence, the number of network carriers operating has been reduced in the domestic U.S. market. In addition, network carriers have widely used regional airlines on their low-density and short routes, because of the cost advantage of regional airlines. Although regional airlines operate aircrafts with a higher cost per available

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[1] […there are "three carrier groupings: network, low cost, and regional. Network carriers use a traditional hub-and-spoke system for scheduling flights. Low-cost carriers operate under a generally recognized low-cost business model, which may include a single passenger class of service, standardized aircraft utilization, limited in-flight services, use of smaller and less expensive airports, and lower employee wages and benefits. Regional carriers provide service from small cities and primarily use smaller jets. Regional carriers are also used to support larger network carrier traffic into and out of smaller airports to the network carriers' hub airports.] Available at: http://www.bts.gov/publications/journal_of_transportation_and_statistics/volume_08_number_01/html/data_review/index.html

[2] Calculated based on US Department of Transportation's T100 market data, http://www.transtats.bts.gov/Fields.asp?Table_ID=258.

seat miles (Forbes and Lederman, 2007), they still maintain cost advantages due to smaller break-even load factors on those limited capacity routes and to lower wage costs[3]. As a result, regional airlines have already been flying a significant part of the U.S. airline market, operating over 46% of annual total departures by 2014[4].

There is a variety of possible vertical relationships between regional airlines and network airlines. For example, regional airlines are mostly independent, providing most of their capacity under capacity purchase agreements (CPAs) with one or more network airlines. On the other hand, a few regional airlines are (or have been) wholly owned by network carriers. For example, Piedmont Airlines is a fully owned subsidiary of American Airlines, and Endeavor Air is owned by Delta Air Lines. From a business standpoint, executives need to figure out whether outsourcing to independent regional airlines or operating owned regionals best benefits network airlines. There is, however, scarce research on the impact of such practices on network airlines' performance (e.g. revenues or profits). This study fills the gap by exploring whether vertically integrated regionals and outsourced independent regionals have different impacts on network airlines' performance.

Profitability consists of two essential components: revenue and cost. While on the cost side, as discussed earlier, regionals enjoy some advantages over network airlines (e.g., lower labor costs), academic researchers have overlooked what effect practices regarding outsourcing regional flights could have on the network airline's demand and, consequently, revenues. To explore the effect of vertical relationships on

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[3] Hirsch (2007) finds that United Airlines' senior pilots earn 80 percent more than senior pilots at regional airlines. Senior flight attendants and mechanics earn 32 percent more and 31 percent more than their counterparts at regional airlines, respectively.

[4] It is from Regional Airline Association (RAA) 2015 Annual Report. Available at http://viewer.epageview.com/Viewer.aspx?docid=21761cad-27ae-4222-b106-a52900d59c80#?page=18

demand, it is necessary to analyze passenger perspectives on owned versus independent regional airlines. Anecdotal evidence suggests that passengers have shown doubts with regional airlines on different aspects, such as safety standards[5], perception of comfort, factors such as stage length and aircraft type, quality of customer service[6], etc. Therefore, operating regional flights instead of network mainline flights on a route could potentially hurt the network airline's demand. However, it remains unclear whether passengers differentiate between owned regionals and independent regionals.

In practice, major U.S. network airlines have started to attend to the negative impact of using regional airlines, with the main focus on firm reputation and customer satisfaction. In 2012, Delta discontinued its owned regional carrier, Comair, and reduced the total number of regional airlines while adding more mainline flights in its network, together with the claim: "While regional flying has and will remain a key component of Delta's network, customer expectations and the unit costs of regional flying have evolved" (Baysden, 2012). Nevertheless, the direction of actions is not unanimous. Also in 2012, American Airlines Group (parent company of American Airlines) outsourced more of its regional business, previously operated by its owned regionals, to independent regionals, in an effort to restore profitability (Cameron and Incas, 2012).

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[5] Questions about safety standards were raised on regional airlines after a federal investigation concluding safety violations by the pilots of Colgan, an outsourced flight of Continental Airlines, killing 50 people at the incidence on Feb. 12, 2009. Available at http://www.wsj.com/articles/SB124217348431613081

[6] For example, according to the Department of transportation, in August 2009, the bottom five airlines in baggage handling were regional airlines. Available at http://www.wsj.com/articles/SB10001424052748704252004574459083159765074

In this study, we examine the passenger choice between ticketing network carriers when flights are operated by either owned or independent regional airlines or by the network carriers themselves. We investigate determinants of passenger choice using data on United Airlines and American Airlines on duopoly routes from the carriers' common Chicago hub, O'Hare Airport. The estimation of our choice model is based on archival data from Origin and Destination Data (DB1B) and on the Airline On-Time Performance dataset, which will be discussed in detail in the data section.

A significant number of studies in the airline industry have focused on the determinants of passenger choice of airlines (Proussaloglou and Koppelman, 1995; Suzuki, 2004). Passenger choice has been found to be dependent on various factors categorized as airline characteristics, passenger characteristics, and/or trip characteristics. More specifically, airline fares, and frequency of service among other factors have been established as major determinants of passenger choice. Besides these well-recognized factors, our choice model introduces variables of network airline flights, owned and independent regional flights, as well as the carriers' recent history of on-time performance on their competitive routes. We examine customer preferences for owned regional over independent regional flights when making carrier choices.

Our main finding is that passengers prefer network airlines' owned regional flights over independent regional flights, even after we control some airline level factor. More importantly, our main finding implies that a network airline, as the ticketing airline, could increase its demand by switching from outsourced independent regionals to owned regional airlines, holding other factors unchanged. In addition, we find that passengers prefer network mainline flights over regional flights, which is consistent with anecdotal evidence, as discussed earlier. Finally, no effect of delay history was found.

Our study has its contributions in the following aspects. First, it is by our knowledge the very first attempt in academic research to quantify the effect of owned versus independent regional airlines on network airlines' demand. We differentiated in-house regional flying with outsourced independent regional flying, which represent two different operational forms by network carriers. We have found that using owned regional airlines benefit a network an airline's demand compared with using independent regional airlines. Secondly, our findings add empirical evidence to the outsourcing literature that vertical integration has a positive impact on firm's demand. Theoretical work predicts that outsourcing can have a direct impact on firm performance, for example, the transaction cost theory by Williamson (1975, 1985), and the incomplete contract theory by Grossman and Hart (1986) and Hart and Moore (1990). However, there is no clear empirical evidence in the literature (Lafontaine and Slade, 2007). Previous research either has no clear answers about the impact of outsourcing on firms' overall performance (e.g., demand and profit) (Kosová et al., 2012), or only has findings of outsourcing on firms' operational performance (e.g., service quality) (Forbes and Lederman, 2010; Novak and Stern, 2008). Thirdly, previous research on airline choice is generally based on limited passenger survey data (e.g., Proussaloglou and Koppelman, 1995; Yoo and Ashford, 1996; Suzuki, 2004). We collect archival data of passengers' choices (i.e., airline market demand data) in a duopoly market, which makes our results more objective, and replicable. Finally, as shown in our scenario analysis, we believe our findings could have strategic implications for managers to understand the consequences of outsourcing regional flights on network airline performance.

The rest of this chapter is organized as follows. Section 2 introduces the background of regional airlines as well as our focus market. Section 3 performs a literature review and describes our conceptual model. Section 4 introduces our model and estimation procedures. The data are discussed in Section 5. The empirical results and scenario analysis are presented and discussed in Section 6 with concluding remarks provided in Section 7.

2.2 Industry Background

2.2.1 Regional Airlines in U.S.

Regional airlines in the United States provide service to network airlines on short and low-density routes, and connect small cities with network airlines' hubs. Nowadays, almost all regional airlines are contracted with network airlines. Under these contracts, a regional airline operates flights with its own planes, pilots and flight attendants on behalf of a network airline, while the network airline tickets these flights. In particular, the regional airline paints its planes using the same logo as the network carrier's fleet; and flight attendants of the regional airline wear the network airline's uniforms.

Network airlines do not operate small aircraft. They contract short and low-density routes to regional airlines, which operate small aircraft (e.g., normally with fewer than 90 seats), mainly due to regional airlines' cost advantage. For example, Hirsch (2007) found that United Airlines' senior pilots earn 80 percent more than senior pilots at regional airlines. Senior flight attendants and mechanics earn 32 percent more and 31 percent more than their counterparts at regional airlines, respectively.

Even though aircraft operated by regional airlines have higher cost per available seat mile (Forbes and Lederman, 2007), regional airlines still maintain cost advantage due to smaller break-even load factors and the lower wage cost. Nevertheless, the cost benefit has decreased recently at a time when a pilot shortage has become a big challenge for regional airlines ever since the new federal regulations governing commercial airline pilots came to effect. Now the minimum flying hours for pilots to be considered for hire has increased from 250 hours to 1,500 hours, a change that invites higher income to compensate for the higher cost of civilian pilot training, and consequently a pilot shortage for regional airlines[7].

Organizational Forms

The relationship between network airlines and regional airlines has the following two organizational forms. On one hand, a regional airline could be fully owned by a network airline. For example, Envoy Air[8] is a wholly owned subsidiary of the American Airlines Group. In this case, the two carriers can be considered to be vertically integrated (Forbes and Lederman, 2007; Forbes and Lederman, 2009). On

[7] Delta is suing its outsourced regional airline, Republic, in Dec. 2015, for unable to fulfill the contract exactly because of pilot shortage. Available at http://www.myvirtualpaper.com/doc/coeur-d-alene-special-sections/newspaper/2016010101/14.html#14

[8] Envoy Air was branded as American Eagle Airlines before January 15, 2014.

the other hand, a regional airline could be independent, contracted with one or more network airlines. For example, both Delta Air Lines and United Airlines outsource regional flights/routes to Mesa Airlines, an independent regional. See Table 2.1 for partnerships between network and regional airlines.

Even though both owned and independent regionals have obvious cost advantages over network airlines, owned and independent regionals may have different operating cost. When a regional airline is wholly owned by a network airline, regional employees may demand wages closer to that earned by their counterparts at the network airline (Forbes and Lederman, 2007).

In addition, the majority of contracts between network airlines and independent regional airlines have transferred from “revenue-sharing agreements” to “capacity purchase agreements” (CPA) since the late 1990s[9]. Under these CPA agreements, a network airline retains all ticketing revenue and pays a fixed amount to buy regionals’ service capacity on a flight-hour basis. Payments to regional airlines are contingent on their route performance (e.g., on-time performance). However, these contracts are incomplete since there is, at least, no coverage on real-time schedule adjustments (Forbes and Lederman, 2010). For example, when there is a schedule change due to severe weather condition or operational disruptions, independent regional airlines may have less incentive to comply with the major’ requests compared to owned regionals.

9 Relevant information can be found in the American Institute of Certified Public Accountants (2007).

Table 2.1 Network and Regional Partners in 2015

Network Airline	Regional Airline Partners
American Airlines	Air Wisconsin
	Envoy Air (formerly **American Eagle**)
	ExpressJet Airlines
	Mesa Airlines
	Piedmont
	PSA
	Republic Airlines
	SkyWest Airlines
	Trans States Airlines
Delta Air Lines	Compass Airlines
	Endeavor Air
	ExpressJet Airlines
	GoJet Airlines
	Shuttle America
	SkyWest Airlines
United Airlines	Cape Air
	CommutAir
	ExpressJet Airlines
	GoJet Airlines
	Mesa Airlines
	Republic Airlines
	Shuttle America
	Silver Airways
	SkyWest Airlines
	Trans States Airlines

Note: Regional airlines in bold are wholly owned by the network partners
Source: Regional Airline Association (www.raa.org)

2.2.2 Focus Market

There is a well-established body of literature investigating competition among network carriers. Many of the studies have used data on United Airlines (UA) and American Airlines (AA) on routes originating from Chicago's O'Hare Airport (ORD) (e.g., Brander and Zhang, 1990; Oum, et al., 1993). We follow these studies and collect data on 32 routes originating from ORD for three major reasons. Firstly, Chicago's O'Hare Airport has been one of the busiest airports in the world for dozens of years. According to the statistics reported by the Chicago Department of Aviation (CDA): "In 2014, O'Hare was the busiest airport in the world in terms of number of annual aircraft operations."[10] In terms of its importance to network carriers being analyzed in our study, it is the largest hub for United Airlines (in terms of departures) and the second-largest hub for American Airlines.

Secondly, the two network carriers, UA and AA, compete as a duopoly on several routes from their common hub at O'Hare Airport. This type of competition has been well studied in previous research as an example of Cournot competition (Oum, et al., 1993). Thirdly, we have observed differentiated operations of regional flying with these two network carriers in this market, which is a prerequisite for our analysis. To be specific, for the period of time for our sample, for the 32 duopoly routes originating from ORD, UA uses either mainline flying, or outsourcing to regional airlines, while AA operates either its mainline equipment or with American Eagle, a regional carrier, then fully owned by AA. These different operations are consistent with the findings by Brander and Zhang (1990) that both carriers' fares

[10] Besides, in 2010, O'Hare was the third busiest in terms of number of annual passengers. Available at http://www.flychicago.com/OHare/EN/AboutUs/Facts/Pages/Air-Traffic-Data.aspx

tend to exceed marginal costs on their routes from Chicago, suggesting a healthy market which leaves the room for these airlines to differentiate their services in order to achieve these mark-ups, where examples of differentiation strategies include price differentiation (Oum, et al., 1993), and use of owned versus independent regional flights.

2.3 Literature Review

There are at least three areas of literature related to this study. The first area of literature focuses on regional airlines in the airline industry. The second area is concerned with passenger choice among airlines. Finally, the third area is concerned with empirical studies on the impact of outsourcing on firm performance.

2.3.1 Regional Airlines

In the airline literature, studies on regional airlines mainly focus on (1) the rationale of using owned and/or independent regional airlines by network airlines; and (2) the impact of different regional airlines' vertical relationships with network airlines on network airline performance.

There are several reasons network airlines choose different organizational forms. First, previous research contends that regional airlines have cost advantages over network airlines to operate on short and middle haul (below 1500 miles) and low-density routes (Forbes and Lederman, 2007; Forbes and Lederman, 2009; Forbes and Lederman, 2010). Gillen et al. (2015) find that cost differences between network airlines, and cost differences between regional and network airlines, are main determinants of a network airline's decision on whether to outsource regional flights. Secondly, Forbes and Lederman (2009) argue that network airlines have incentives to choose vertical integrated regionals on those routes where real-time adjustments to schedule disruptions are needed. That is, ownership of regional airlines provides networks airlines more power to align different interests when adaptation decisions are needed. Finally, Levine (2011) mentions that there exist a variety of firm structures among network airlines post deregulation. No single structure dominates, while organizational forms have changed over time under different conditions.

On the other hand, the impact of using owned and/or independent regionals on network airlines' performance has been scarcely explored empirically. From a business point, executives need to understand whether outsourcing to regionals or operating by owned regionals improves a network airline's performance (e.g., market share and revenue). Forbes and Lederman (2010) choose an indirect performance measure as on-time performance. The authors find that network airlines using owned regional airlines have systematically better on-time performance over those network airlines using independent regionals. No paper has yet applied a direct measure to assess the performance of owned versus contracted commuter affiliates. Thus, this study adds empirical insights by exploring how these different vertical relationships between regionals and network airlines impact network airlines' performance by using direct performance measures (i.e., market share).

Finally, there is scarce research on passenger perspectives on regional airlines. Using survey data, Truitt and Haynes (1994) find evidence that passengers prefer network flights over regional flights due to fleet size concern, which is assumed to be a signal of service quality. As in most high-customer-contact service industries, passengers as end-customers are core in airline industries. Those questions are kept unanswered: whether passengers have different preferences over owned versus independent regionals; and how the different preferences may affect network airline performance.

2.3.2 Passenger Airline Choices

A main stream of passenger choice research is based on stated preference survey data. The survey data on airline passengers provide detailed information about passenger demographics (e.g., age, gender, income) and trip purpose (e.g., business vs leisure). Studies have found passenger choice depends on airline-specific, passenger-specific, and route-specific characteristics (Proussalogou, and Koppelman 1995). Factors that have been identified as influential include airfare, travel time, frequency of service and, on-time performance (Yai, et al. 1997; Yoo and Ashford 1996). Yoo and Lee (2002) have further added seat availability to the relevant list of factors. In addition, the authors have found that the relevance of the factors in determining passenger choice depends on traveler characteristics. For example, business travelers place more emphasis on on-time performance than do leisure travelers. Finally, Toh and Hu (1988) ask frequent travelers to rate eight factors they consider important in airline choice. They report that, in order of importance, the first five are: (i) convenience of schedules, (ii) on-time performance, (iii) low or discount fares, (iv) overall service by attendants, and (v) frequent flyer programs.

Note that even though airline on-time performance is a popular measure of airline operational performance, findings for the effect on passenger choice remain mixed. Suzuki (2000) concludes that on-time performance affects a carrier's market share primarily through the passengers' experience. However, Suzuki (2004) has not found any significant connection between passenger airline choices and past service failure experience.

Stated preference data collected by surveys has the advantage of providing detailed information of decision makers (e.g., travel purposes and frequent flyer programs). However, it suffers from strong subjectivity and a risk of response bias. A very limited stream of research on passenger airline choice, like our study, is based on empirical archival data. Among these papers, using Airline Origin and Destination Survey (DB1B) data from the U.S. Department of Transportation, Berry (1992) uses a structural discrete choice model to estimate entry for the airline industry. Berry and Jia (2010) use a structural model to estimate the change of passenger preferences and its impact on airline's profitability in the early 2000s. Ciliberto and Tamer (2009) use an entry model to investigate heterogeneity in airlines profits. Our study is different in the sense that we are the first to introduce an empirical measure of vertical relationships between regional and network airlines to examine passengers' responses.

2.3.3 Outsourcing and Firm Performance

Researchers have used various theoretical perspectives to understand outsourcing. Some main theories include the transaction cost theory by Williamson (1975, 1985), and the incomplete contract theory by Grossman and Hart (1986) and Hart and Moore (1990). For example, from a transaction cost economics standpoint, outsourcing activities to outsider providers rather than internalizing these activities within the firm allows firms to lower transaction costs. According to incomplete contract theory, outsourcing is that clients employ providers to perform certain activities. The risks of opportunism and moral hazard that remain in such incomplete contracts can lower the expected returns. In general, theoretical work predicts that outsourcing should have a direct impact on firms' performance.

However, there exists no clear empirical evidence on the outcomes of outsourcing in the literature (Lafontaine and Slade, 2007). It is mainly because outsourcing decisions are typically endogenous. Firms may choose outsourcing based on the strategy that they expect to give the best outcome. This optimizing behavior raises endogeneity issues when assessing the effect of outsourcing on firms' performance (Masten, 1993).

Among those empirical studies using archival data, most are industry-based studies. The findings are mixed. For example, Kosová et al. (2012) use a panel data in the hotel industry and has found very small effect of outsourcing on firms' performance (e.g., price and revenue). After, however, controlling endogeneity, the effect turns out to be insignificant. Novak and Stern (2008) choose an indirect performance measure, customer ratings of automobile systems. The authors find that integrated firms have higher ratings over long time than outsourced firms. Forbes and Lederman (2010) also use an indirect performance measure, departure delays of network airlines at airports, and find that using own regional airlines has better on-time performance for a network airline than using independent regional airlines. Similar as Forbes and Lederman (2010), our study also investigates the impact of using owned and/or independent regional airlines on network airlines. But our study is different in two aspects: (1) our study uses a direct performance measure (i.e., market share); (2) our study is based on a customer choice model rather than a firm-level regression model.

In general, out study contributes to all three areas of literature. First of all, we are the first to empirically examine how using vertically integrated regionals versus independent regionals affect network airline demand, and consequently, revenue implications in the airline literature. Secondly, our study uses revealed preference data and examine vertical relationships between regional and network airlines from passengers' perspective. Finally, this study contributes to outsourcing literature by providing empirical evidence of the effect of outsourcing on a firm's direct performance measure (e.g. demand).

2.4 Choice Model and Estimation

2.4.1 Conceptual Model

The conceptual model for our study is shown in Figure 2.1.

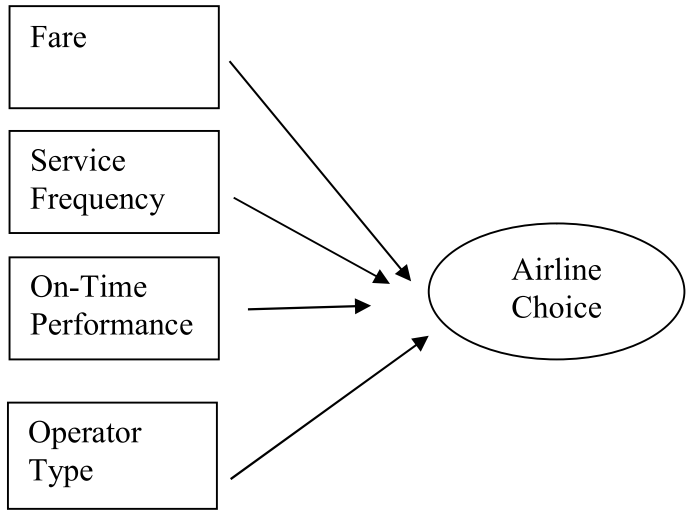

Figure 2.1 A Conceptual Model of Passengers' Airline Choice

As indicated in the above figure, we introduce four airline-specific factors in our passenger choice model.[11] In addition to airline fare, service frequency, and on-time performance, all three identified as key factors in determining airline choices in theliterature, we also include the operator type dummy variable that accounts for passengers' preference over different operator type (i.e., mainline flights, owned regional flights or contracted independent regional flights). More detailed variable descriptions are provided in the data section.

2.4.2 Aggregate Logit Model

We model passenger choice behavior using a multinomial LOGIT (MNL) model (Ben-Akiva and Lerman, 1985). However, our model differs from standard models in the way that we control for unobserved characteristics, in that we assume the model

[11] Although we acknowledge that passenger-specific characteristics, such as trip purpose (e.g., business vs. leisure), frequent-flier membership, and perceptions of airline services, all will affect a passenger's choice of airlines, we exclude these factors from our model since we use aggregate-level data. As a result, we factor passenger-specific variables as unobserved factors in our choice model.

contains a second error term. For airline j in market k, the utility of passenger i is given by:

$$u_{ijk} = x_{jk}\beta - \alpha p_{jk} + \eta_{jk} + \xi_{ijk} \qquad (1)$$

where

- x_{jk} is a vector of airline characteristics,
- β is a vector of parameters for passengers,
- α is the marginal disutility of a fare increase for passengers,
- p_{jk} is the average airline fare for airline j in market k,
- η_{jk} is the unobserved (to researchers) characteristic of airline j,
- ξ_{ijk} is an i.i.d. (across airlines and passengers) "logit error".

Here, we assume all passengers have homogenous preferences over all airline characteristics; that is, α, β are the same for all passengers. The first error term η_{jk} captures unobserved factors (to researchers) that affect carrier choice, such as ticket restrictions, time of departure, and membership in an airline's frequent flier program, as discussed in the conceptual model. Since these factors are observable to the passenger, they may influence his/her airline choice. However, because they are unobservable to the researcher, they will contribute to errors in the model. Furthermore, these factors are likely to be correlated with the airline fare, leading to endogeneity concerns. Finally, to keep the model tractable, we assume that these unobserved factors are independently distributed across all airlines.

In MNL models, adding a constant to every utility value does not change choice probabilities (Ben-Akiva and Lerman, 1985). To make the choice model uniquely identifiable, we have to set an outside option as a reference level. The outside option can be thought as other modes of transportation, as well as the option of not traveling at all. Following the general setting in MNL models, the utility of the outside option is given by the following equation:

$$u_{i0k} = \xi_{i0k}. \qquad (2)$$

where ξ_{i0k} is a second error term in the model. Thus the market share of airline j in market k is given by the following:

$$S_{jk} = \frac{\exp\left(x_{jk}\beta - \alpha p_{jk} + \eta_{jk}\right)}{1 + \sum_{m=1}^{J} \exp\left(x_{mk}\beta - \alpha p_{mk} + \eta_{mk}\right)}, \qquad j = 1, \dots, J \qquad (3)$$

where J is the total number of airlines on a market. The probability share of the outside options is given by the following:

$$S_{0k} = \frac{1}{1 + \sum_{m=1}^{J} \exp\left(x_{mk}\beta - \alpha p_{mk} + \eta_{mk}\right)}. \qquad (4)$$

Therefore, we can calculate the log odds ratio as shown in Equation 5:

$$\log\left(\frac{S_{jk}}{S_{0k}}\right) = x_{jk}\beta - \alpha p_{jk} + \eta_{jk}, \qquad j = 1, \dots, J. \qquad (5)$$

Endogeneity

Once we have the relative market share (or relative demand) of airlines (S_{jk} / S_{0k}) in market k from our aggregate demand data, we can estimate (β, α) in the linear equation (5). However, as mentioned earlier, there is concern over endogeneity due to correlation between airline fare and the unobserved factors, η_{jk}. In addition, flight frequency, as with fare, has endogeneity issues due to the fact that airlines can strategically change frequency and fare on any route.

Estimation

To ensure consistent estimation of Equation (5), we need instrumental variables to identify both fare and frequency coefficients. We can write down the moment conditions used for the estimation as the following:

$$E(\eta_k \mid z_k) = 0, \qquad (6)$$

where

- z_k is a vector of instrumental variables, independent of the unobserved factors, η_k.

These moment conditions imply

$$E(h(z_k)\eta_k) = 0, \qquad (7)$$

for any vector functions $h(\bullet)$. We use generalized method of moments (GMM) to find parameters (β, α) to make the moment condition in Equation (7) as close to zero as possible. Note that if we assume that η_k is independently distributed as a normal distribution across different markets k, the GMM is actually a two-stage least squares estimation. By using GMM, we do not need to assume the specific distribution for the error term η_k.

As in typical demand studies with endogenous prices, we need instrumental variables to identify the fare and frequency coefficients. Common instruments exploit the rival product attributes and how competitive the market is. The instrumental variable set should also include all exogenous variables in the model that would help us to predict endogenous variables. Our selection of specific instruments are discussed in the next section, after we introduce the data in more details.

Finally, if we omit endogeneity issues, the model in Equation (5) is actually an ordinary least squares (OLS) model. It is expected that ignoring endogeneity due to potential correlation between error terms and fares could bias the estimation results. Thus, in our estimation, we keep the estimation results by OLS as a base model and then compare these results with the estimation results of our aggregate logit model that controls for endogeneity.

2.5 Data

2.5.1 Sample Selection

There are two main data sources for this study. The first is the Origin and Destination Survey (DB1B), which consists of a 10% sample of tickets sold by all domestic airlines. The Bureau of Transportation Statistics (BTS) collects detailed data on fares and the number of passengers transported, and reports these data in DB1B on a quarterly basis (i.e., four times per year). Each observation in the sample contains the origin and destination of that particular passenger, the ticketing and operating airline for each segment, the fare paid by the passenger, as well as detailed information on any connections made on the route to the final destination. We aggregate this set of data to the airline-origin-destination level, and construct the average airline fare and the airline market share in a market over a quarter based on individual passenger observations. We then use data from the Regional Airline Association (RAA) to identify whether or not a network airline's regional partners is owned by that network airline.

The second data source is the Department of Transportation's Airline On-Time Performance dataset that contains daily information about the scheduled and the actual departure and arrival times for each individual flight. Each observation contains the origin and destination as well as the operating airline. All airlines that account for at least 1% of domestic passenger revenues in the prior year are required to report their flights at all airports that account for at least 1% of domestic passenger enplanements. We construct various aggregate measures of flight delay from this dataset and match these delay statistics to the fare and market share data from DB1B.

2.5.2 Market Definition

In this study, we model a market as a directional pair of origin and destination airports. For example, Chicago O'Hare – Denver is a different market from Denver – Chicago O'Hare. We pick airport pairs with a distance less than 1500 miles. These airports pairs could be operated by a regional airline with its aircraft fleet (Forbes and Lederman, 2009). We restrict the sample to round-trip, direct-flight, and coach-class tickets.

We eliminate indirect-flight tickets from our sample because (1) passengers taking connecting flights are assumed to have different utilities from those taking direct flights; and, (2) due to data limitation, there is no clear way to construct and interpret measures of flight frequency and on-time performance for connecting flights composed of two or more flight segments (Berry and Jia, 2010).

For our observations (carrier- and route-specific quarterly data points), following the existing study by Oum et al. (1993), we only consider routes originating from Chicago O'Hare Airport (ORD), in which ticketing carriers AA and UA have a combined market share exceeding 96 percent (i.e., passengers on direct round-trip flights in a duopoly market). Note that the underlying assumption is that passengers have already made up their mind to take direct round-trip flights from O'Hare to a destination. In these experimental markets, we explore how passengers differentiate between owned regional flights and independent regional flights. Furthermore, each airline has at least 30 percent of the combined share, and the quarterly traffic volume for each airline in the 10 percent sample is at least 100 passengers. With all these conditions satisfied, we consider these routes to be duopoly markets for AA and UA (Oum et al., 1993).

There is another airport, Midway, located in the Chicago area. However, over 80% of passengers at Midway are on flights operated by low-cost airlines. In this study we focus on network airlines that are different from those low-cost airlines. Zou, Dresner, and Windle (2011) also find that network carriers tend to compete with other network carriers. Following Borenstein (1989) and Brander and Zhang (1990, 1993), we assume that flights to Midway and O'Hare airport are in separate markets.

Admittedly, our sample is a subset of the U.S. airline market. A national sample would provide a wider picture of passenger preferences. However, our selected sample has the following advantages: First, our defined markets all originate at Chicago O'Hare airport. The characteristics of origin city will affect demand and failing to control for the characteristics of the origin airport has the potential to bias the estimation results. This could be the case if a national sample with many origin airports was used. Our sample is free from this concern. Secondly, in our markets, AA and UA can be viewed as symmetric firms with similar cost structure and brand images (Brander and Zhang, 1990). Other network airlines and low-cost airlines have only negligible market shares on those routes. Therefore, passengers are faced with relatively fixed choice sets (i.e., buying tickets from either AA or UA) across all our markets.

Moreover, all markets in our sample falls into one and only one of the four possible scenarios for operating carriers: (1) UA and AA; (2) UA regional affiliates and AA; (3) UA and AA regional affiliates; (4) UA regional affiliates and AA regional affiliates. As an example, in a market, round-trip direct flights between O'Hare and Oklahoma City, AA tickets those flights operated by its fully owned regional airlines, that is, American Eagle; while UA tickets those flights operated by a few independent regional airlines. We do not consider scenarios where both the network carrier and its regional affiliate together serve on a given route. This definition helps us to perfectly differentiate the operating carriers from each other and from their regional affiliates. In addition, we also found confounding cases with mixed network flights and regional flights to be very rare in our sample.

To summarize, our data contain 240 quarter-route level markets from 2003 to 2009, for a total of 480 observations (i.e., two observations per market and one for each ticketing airline). Finally, our panel data are unbalanced consisting of 32 routes and 27 quarters.

2.5.3 Variables

A number of variables are constructed from the above-mentioned sample dataset and used in the empirical analysis to follow.

Market Share

Market share reflects the aggregate choices of passengers when choosing between airlines operating on a route. In order to construct a meaningful measure of the size of a market, we collect data on the population of each Metropolitan Statistical Area (MSA) from the Bureau of Economic Analysis's Regional Economic Accounts database. Similar to Berry et al. (2006) and Lederman (2007), we match these figures with the corresponding airports and define the size of a particular market as the geometric mean of the populations at the market's endpoints.

We then define the market share S_{jk} as the total number of passengers choosing product, j, in market, k, (from the DB1B quarterly data), divided by the size of the market.

Airline Fares

The data on fares is used to construct market-quarter-airline specific measures of the price charged by an airline. Specifically, *Fare* is the average fare on a given route charged by a particular ticketing airline (American or United) averaged over all customers in a market over a quarter. If the ticket is issued for a round trip, the fare is divided by two. Similar to Berry and Jia (2010), a small proportion of the tickets have been removed from the sample in order to avoid potential misreporting of the data. For example, tickets with fares of less than $25 are assumed to be either reserved by airline employees or paid for frequent flyer trips, rather than purchased by fare-paying passengers. It is predicted that higher fares will lead to lower market shares for a carrier on any given route.

Airline Flight Frequency

We construct *Frequency* as the average number of direct flights per day for an airline in a particular market. Data were gathered from the Department of Transportation's on-time performance dataset. This measure reflects the convenience of an airline's schedule to passengers. The higher an airline's flight frequency, the greater the chance that a passenger chooses to fly with that airline.

Operator Type

We construct dummy variables, *Owned_regional*, and, *Indep_regional*, to differentiate owned regional airlines from independent regional airlines. The reference dummy is *Network*, indicating flights operated by a network airline itself. In our sample, AA only used its owned regional, American Eagle, while UA used a few independent regional airlines (conducting business as United Express). In addition, since AA and American Eagle belong to the same parent company, we refer to them as vertically integrated. On the other hand, United Express consists of independent regional airlines operating flights for UA. Both dummies equal to 1 if all flights are operated by regional carrier affiliates, while equal to zero if all flights are operated by the network carrier itself. We also introduce a ticketing airline dummy, *AA* to control ticketing network airlines' branding effects. In addition, we assume that passengers, when given a choice, prefer to fly on aircraft operated by the network carrier. Therefore, it is expected that both *Owned_regional*, and, *Indep_regional*, will have negative impacts on carriers' market share.

According to the findings of Forbes and Lederman (2009, 2010), regionals vertically integrated with network airlines (e.g., American Eagle and AA) have better operational performance compared with those independent regionals. In addition, Novak and Stern (2008) conclude that the higher vertical integration level, the higher the customer satisfaction level. Therefore, we propose hypothesis that *Indep_regional* has a stronger negative effect on network carriers' market share than does *Owned_regional*.

On-Time Performance

We aggregate the delay statistics across all operating airlines for a ticketing airline on a route over a quarter to calculate on-time performance. For example, in a market, a few independent regionals operate flights for UA. We first construct on-time performance for each independent regional operator. We then generate overall on-time performance for the ticketing carrier, UA, in this market by weighting the number of departures by each operating independent regional airlines. The underlying assumption is that passenger choices are affected by his/her past experiences in this market with the ticketing airlines. Note that we lag flight delay measures by one quarter in our model since we assume that a passenger's observation of past on-time performance will affect his/her current choice among airlines.

We construct flight delay measures in four ways. The first measure, *PerDelay*, is the fraction of flights operated by any airline on a given route within a quarter that arrive at the destination more than 15 minutes delayed. This is also the measure that the Federal Aviation Administration (FAA) uses in its published on-time statistics. *PerDelay* can be interpreted as the probability of a flight arriving later than an accepted length of delay. In addition to the fraction of delayed flights, a second measure, *ArrDelay1*, is calculated as the average minutes of arrival delay per flight at the destination during the quarter. Early arrivals are counted as zero delays. Another similar measure, *ArrDelay* counts early arrivals as negative number as in the original data. The last measure, *cancel*, is the percentage of flights cancelled over total planned flights during the quarter. For all the measures, we expect that delays will negatively affects the market share for an airline.

Finally, to control for market heterogeneity, we include a *distance* (i.e., direct distance between origin and destination) variable to capture the variability of passengers' mean utility across different markets.

2.5.4 Data Summary

Statistics on these variables are summarized in Table 2.2, grouped by ticketing airlines. From Table 2.2, AA has slightly lower average fares and lower flight frequencies compared to UA. We note that the average delay time for AA is less than that for UA. However, AA has a higher percentage of flights late more than 15 minutes and a higher percentage of cancelled flights compared with UA. In general there is no clear signs as to which airline has better on-time performance. Approximately 24% of routes are served by owned regional operators, and 29% by independent regional airiness in our sample.

Table 2.2 Summary Statistics for the Data Set

	AA		**UA**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Fare ($100)	1.522	0.327	1.562	0.315
Frequency (No. of flights per day)	6.323	4.083	6.624	4.298
Distance (100 miles)	7.802	2.323	7.802	2.323
ArrDelay (min. per flight)	11.929	7.517	12.167	9.022
ArrDelay1 (min. per flight)	17.547	6.190	18.205	8.010
PerDelay (%)	26.554	7.868	25.815	8.117
Cancel (%)	0.029	0.024	0.024	0.025
Owned_regional	0.238	0.426		
Indep_regional			0.292	0.455
Observations	240		240	

Table 2.3 Comparing Performance of Owned and Independent Regionals

	Owned Regionals		**Independent Regionals**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
ArrDelay (min. per flight)	12.944	6.76	11.185	9.859
ArrDelay1 (min. per flight)	17.301	5.621	18.098	8.621
PerDelay (%)	28.549	8.094	24.966	7.696
Cancel (%)	0.036	0.023	0.031	0.031
Observations	57		70	

We further compare on-time performance between owned and independent regional airlines, as shown in Table 2.3. There is no significant difference with regard to the on-time performance between the two different types of operators on average.

Table 2.4 Pearson Correlations

	Fare	Frequency	Distance	PerDelay	ArrDelay	ArrDelay1	Cancel	Owned_ regional	Indpep_ regional
Fare	1								
Frequency	0.222*	1							
Distance	0.343*	-0.070	1						
PerDelay	0.039	0.093	0.074	1					
ArrDelay	0.006	0.098	0.059	0.932*	1				
ArrDelay1	0.046	0.115	0.089	0.903*	0.979*	1			
Cancel	0.151	0.327*	-0.276	0.297*	0.272*	0.288*	1		
Owned_ regional	0.113	-0.148*	-0.396*	0.109	0.040	-0.029	0.133*	1	
Indept_ regional	-0.014	-0.381*	-0.313*	-0.063	-0.043	0.013	0.073	-0.152	1

*. Correlation is significant at the 0.01 level (2-tailed)

Pearson correlation coefficients are calculated and shown in Table 2.4.

In Table 2.4, *PerDelay* , *ArrDelay* and *ArrDelay1* are all highly correlated (over 0.9), indicating that these three on-time performance measures are consistent. Another on-time performance measure in our data, *cancel*, seems not to be consistent with other measures (below 0.3). *Indep_regional* is negatively correlated with *Frequency* (-0.381), which is consistent with the observation that regional airlines operate routes with fewer flights per day than do network carriers. Moreover, both

Owned_regional and *Indep_regional* are negatively correlated with Distance (0.3~0.4), which is consistent with the observation that regional airlines serve shorter routes than their network carrier counterparts. Previous research found that vertically integrated regional airlines have better operational performance (e.g., on-time performance) (Forbes and Lederman, 2009; Forbes and Lederman, 2010). In our data, there is no clear evidence that regionals and on-time performance are correlated, except for *Owned_regional* and *cancel* (slightly above 0.1).

2.5.5 Instruments

As in typical demand studies with endogenous prices, we need instrumental variables to identify the fare coefficients. One common strategy is to explore the rival product attributes and the competitiveness of the market. However, under our settings, only two airlines compete in each duopoly market. It is infeasible to explore these instruments. Another strategy is to follow Nevo (2000) to exploit the panel structure of the data. It is suggested that prices of a brand in other markets are valid instruments. Prices of brand j from a given firm in two markets will be correlated due to the common marginal cost, but will be uncorrelated with the market-specific valuations of the product. Similarly, we choose the average fare per mile, *FarePerDistAvg*, over all other routes for a ticketing airline as an instrument for its fare on a given route. There are still some situations when the independence assumption might not hold, as discussed in Nevo (2000). Therefore, in this study, we run estimation over different sets of instrumental variables and keep those which provide reasonable results.

The second group of instrumental variables are those that are supposed to affect costs but not demand. *HubDest* is a dummy variable indicating whether the destination is a hub for the ticketing carrier. For example, for flights from Chicago O'Hare to Washington Dulles, this variable is coded 1 for UA and 0 for AA, since Dulles is a UA hub but not an AA hub. On routes with denser traffic, larger more fuel efficient planes can be used which. It will affect the marginal cost (per passenger) of a flight. As a robustness check, we have tried to estimate the model with and without the instruments. There is no significant difference between these estimated parameters.

The third group of instruments, *Fare_Fit*, are the fitted values of fares after regressing fare over characteristics of the end cities. These exogenous variables in the regression are: carrier dummies, route level characteristics (e.g., distance and whether the destination is a tourist city), population size as market size. Instruments for frequency, *Fq_Fit*, follows the same logic as fitted frequency. The fitted fare is finally omitted due to collinearity concerns, while fitted frequency is used in estimation.

Table 2.5 Summary Statistics for Instruments

	Mean	**Std. Dev.**	**Min**	**Max**
FarePerDistAvg ($1/mile)	0.266	0.017	0.221	0.309
Fare_Fit ($100)	1.580	0.191	1.131	1.837
Fq_Fit (No. of flights per day)	6.410	3.474	1.340	15.574
HubDest	0.1125	0.316	0	1
Observations	480			

Other exogenous variables in the demand function are also included. In addition, we include the interaction and second order term of the above variables as long as there is no collinearity problem. We summarize these instruments in Table 2.5.

2.6 Results

2.6.1 Main Model

We estimate the parameters from the moments condition Equation (7), by using Generalized Method of Moments (GMM) estimation. We first run our aggregate logit model with instrument variables as Model 1. In Model 1, we first used *ArrDelay1* as the on-time performance measure. The estimation results from Model 1 are shown in Table 2.6.

In Model M1, the estimated parameter for the *Fare* is negative and significant as expected. To get a sense of the magnitude of the endogeneity issue, we also run another specification, an ordinary least squares (OLS) estimation without unobserved factors, as discussed in the model section. This OLS model has an estimated *Fare* coefficient of -0.971. Compared with our *Fare* coefficient, -1.304, the own price elasticity is over 34% lower than our own price elasticity. Without considering fare endogeneity, the own price elasticity is underestimated.

In addition, in Model M1, the estimated parameter for *Frequency* is positive and significant, indicating that passengers prefer an airline with more flights per day. The estimated coefficient for *Distance* is positive and significant, indicating that passengers are more likely to take flights on longer distance routes with a higher utility. It is also consistent with previous research (Berry and Jia, 2010). In addition, we did not find any significant effect of on-time performance on passenger choice. As discussed in the literature review section, researchers have not agreed on the effect of on-time performance on passenger choice, reporting all mixed findings.

Table 2.6 Estimation Results of Model M1

	M1	
	DV: Logit	
	Coefficient	Std. Error
(Constant)	**-8.381***	0.194
Fare	**-1.304***	0.242
Frequency	**0.094***	0.010
Distance	**0.166***	0.025
Owned_regional	**-0.322***	0.114
Indep_regional	**-0.427***	0.096
AA	**-0.151***	0.024
ArrDelay1	-0.002	0.002
R-square	0.755	

*Significant at the 0.05 level

Further results from M1 show that the estimated coefficient for *AA* is negative and significant, indicating that UA has a better branding effect on the routes being investigated. Both estimates of *Owned_regional* and *Indep_regional* are significant and negative. Since the base case is mainline flights, it supports our hypothesis that passengers prefer network flights over contracted regional airline flights. It is consistent with anecdotal evidence as mentioned in the Introduction and previous research (Truitt and Haynes, 1994) that passengers have questions about the safety performance, convenience and service quality of the regional airlines.

More interestingly, even after controlling for firm-level factors, e.g., branding effects of ticketing carriers and flight frequency, on average, passengers prefer owned regional flights over independent regional flights (-0.322 vs. -0.427). A t-test indicates that their mean difference is significant. The findings provide support to our hypothesis that *Indep_regional* has a stronger negative effect on network carriers' market share than does *Owned_regional*.

In practice, passengers are unlikely to know whether a flight is operated by an owned or independent regional airline. Therefore, a key question is passengers might prefer owned regionals over outsourced independent regional airlines in our sample markets. The underlying reasons may be as follows: First, owned regionals have the incentive to better coordinate with their network partners than do independent regionals (Forbes and Lederman, 2007). Thus, vertically integrated regional airlines potentially have better operational performance and service quality than independent regionals (Forbes and Lederman, 2010). Consequently, passengers may prefer owned regionals over independent regionals. Secondly, it may be argued that in our sample, American Eagle is the only owned regional, and, therefore, our results may be due to the specific airline's attributes. However, in our model, we have already controlled for regional airline firm-level factors; e.g., fare, flight frequency. Moreover, we have (ticketing) airline-specific fixed effects. Therefore, the combination of the fixed effects and the regional-specific variables should work to alleviate this concern.

In general, we conclude that passengers prefer vertically integrated regional airlines over independent regional airlines. Our finding is consistent with previous research that the higher the vertical integration level, the higher the customer satisfaction level (Novak and Stern, 2008). Finally, our study adds a contribution to outsourcing literature that we find empirical evidence that vertical integration has a positive impact on a firm's market share.

2.6.2 Robustness Check

To test whether our findings that on-time performance has no significant effect are dependent on the specific measure of on-time performance, we estimate a series of models with different measures. The other three on-time performance variables are used: (1) Model M2 with *ArrDelay*; (2) Model M3 with *PerDelay*; (3) Model M4 with *cancel*, as listed below.

In general, all estimated parameters are consistent with our main model M1, with no significant effect of on-time performance on passenger airline choice. We also estimate a number of models by adding or removing some variables in the demand equation, and all results are generally consistent. We conjecture that the reason for the insignificant impact of on-time performance is due to our focused markets. AA and UA have similar market power and on-time performance, while customers on these regional routes have similar perceived service quality.

Table 2.7 Estimation Results of Model M2

	M2	
	DV: Logit	
	Coefficient	Std. Error
(Constant)	**-8.398***	0.189
Fare	**-1.314***	0.243
Frequency	**0.095***	0.010
Distance	**0.167***	0.025
AA_regional	**-0.321***	0.116
UA_regional	**-0.429***	0.096
AA	**-0.151***	0.024
ArrDelay	-0.001	0.002
R-square	0.755	

*Significant at the 0.05 level

Table 2.8 Estimation Results of Model M3

	M3	
	DV: Logit	
	Coefficient	Std. Error
(Constant)	**-8.495***	0.193
Fare	**-1.200***	0.240
Frequency	**0.088***	0.010
Distance	**0.151***	0.026
AA_regional	**-0.411***	0.120
UA_regional	**-0.496***	0.099
AA	**-0.148***	0.024
PerDelay	0.003	0.002
R-square	0.766	

*Significant at the 0.05 level

Table 2.9 Estimation Results of Model M4

	M4	
	DV: Logit	
	Coefficient	Std. Error
(Constant)	**-8.415***	0.179
Fare	**-1.270***	0.238
Frequency	**0.093***	0.010
Distance	**0.161***	0.025
AA_regional	**-0.353***	0.112
UA_regional	**-0.452***	0.093
AA	**-0.147***	0.026
cancel	-0.178	0.830
R-square	0.760	

*Significant at the 0.05 level

2.6.3 Scenario Analysis

Based on our estimation results from model M1, we first quantify the effect of using a regional carrier operator on a ticketing airline's market share.

Scenario 1

Suppose that on a route AA and UA operate mainline equipment for all direct flights and equally share the direct-flight market with a 50/50 percent market share (i.e.,

$S_{AA} / S_{UA} = 1$). Now suppose that AA decides to use its regional affiliate; i.e. American Eagle on this route. UA continues to operate only mainline equipment. According to Equation (3), we can calculate the relative probability of choosing AA over UA by using the equation:

$$\frac{S_{AA}}{S_{UA}} = \exp\left(\left(x_{AA} - x_{UA}\right)\beta - \alpha\left(p_{AA} - p_{UA}\right)\right).$$

Assuming that all other characteristics (e.g. fare and frequency) are unchanged, we can calculate the effect of the change to the regional carrier on the relative market shares of the carriers. The share of AA relative to UA (i.e. S_{AA} / S_{UA}) will decrease from $\frac{50}{50} = 1$ to $\exp(-0.322) = 0.725$. Since in a duopoly market $\tilde{S}_{AA} + \tilde{S}_{UA} = 1$, we can solve that $\tilde{S}_{AA} = 0.42$; that is, AA's market share will decrease from 50 percent to 42 percent due to the introduction of vertically integrated regional flights to replace its network flights on the route.

Scenario 2

Now we consider a different scenario. On a route AA and UA operate mainline equipment for all direct flights and equally share the direct-flight market with 50/50 market shares. Now suppose that AA decides to outsource this route to independent regional airlines rather than use its own regional airline, i.e., American Eagle. UA continues to operate only mainline equipment. Assuming that all other characteristics (e.g. fare and frequency) are unchanged, AA's market share will decrease from 50 percent to 40.5 percent due to the introduction of independent regional flights to replace network flights on the route. Compared with Scenario 1, the decrease of market share is $\frac{9.5-8}{8}=18.8\%$ greater.

In general, both scenarios 1 and 2 confirm that using regional operators has a negative impact on a network carrier's market share. In addition, our analysis confirms that the marginal effects of using a regional operator on a network carrier's market share are different for vertically integrated and independent regional carriers. Recall the news discussed earlier that AMR (American Airline's parent company) planned to replace American Eagle with outside independent regional airlines aiming to cut cost. Our analysis suggests the importance for AMR of balancing cost savings from outsourcing with potential demand loss due to replacing a vertically integrated regional with independent regionals.

Scenario 3

As mentioned earlier, regional airlines operate regional jets with available seats normally less than 90, while network carriers use larger aircraft. If a network airline plans to replace mainline equipment with regional airlines on a route, it may have to increase frequency accordingly to meet total capacity requirements.

As in Scenario 1, AA and UA operate mainline equipment for all direct flights and equally share the direct-flight market. Now suppose that AA decides to use its regional affiliate, i.e. American Eagle on this route, and, accordingly, increases frequency by adding four flights per day. Holding all other factors unchanged, the share of AA relative to UA (i.e. S_{AA}/S_{UA}) will increase from $\frac{50}{50}=1$

to $\exp(-0.322+4*0.094)=1.055$. The market share of AA increases from 50 percent to 51.3 percent, rather than decreasing to 42 percent as in Scenario 1. Even though using regional airlines could negatively affect passenger choices, other factors (e.g. frequency) could have positive impacts on market demand. Therefore, to assess the general effect of using regional airlines on demand, executives should consider all associated factors. The scenario analyses are summarized in Table 2.10.

Table 2.10 Summary of Scenario Analyses

Scenario	Pre- market share	AA's Policy change	Post- market share
1	50%	insourcing	42%
2	50%	outsourcing	40.5%
3	50%	insourcing and adding 4 more flights per day	51.3%

2.7 Conclusions

In the U.S. airline industry, there is a trend that regional airlines operate on short stage length and low density routes on behalf of network airlines. In addition, there is variability across and within network airlines over the use of owned and/or independent regional airlines. Little research has explored this area. Most of the existing research examine the rationale and impact of network airlines using vertically integrated or independent regional airlines from the context of cost and/or operational performance differences at the airline level (Forbes and Lederman, 2009;

Forbes and Lederman, 2010; Gillen et al., 2015). However, there are scarce studies to understand how using vertical integrated or independent regional airlines could affect passenger choices and, consequently, network airlines' demand.

Our paper fills this gap as the first study to quantify the impact of using owned and/or independent regional airlines on the network airlines' (ticketed) market share. In addition, there are no clear empirical evidences in the outsourcing literature on the effect of outsourcing on a firm's performance. Our study also adds contributions to this stream of research by exploring the different impact of vertically integrated and independent regional airlines on network airlines' performance (i.e., market share).

In general, our results suggest that passengers prefer network airlines' owned regional flights over independent regional flights. Our scenario analyses confirm that based on our parsimonious model, executives could quantify the marginal effect of outsourcing on market demand. Based on certain assumptions, our model could help executives to assess the consequence of outsourcing. In addition, our findings remind managers to balance the tradeoff between cost savings from outsourcing and potential demand loss as a result of customer preferences.

Our study can be extended in three potential directions. First, as discussed earlier, we need to be cautions in explaining why passengers prefer network airlines' owned regional flights over independent regional flights since passengers are unlikely to know whether a flight is operated by an owned or independent regional airline. Complementary surveys or experimental studies would be helpful to substantiate our findings and further our understanding of passengers' decision processes from a behavioral perspective.

Secondly, it could include customer heterogeneity to provide more realistic estimations. In our model customers are assumed to have same preferences over all factors. In reality, consumer preferences are more complex. Also, given this presumption, the cross elasticity of different carrier flights are always the same, which is also unrealistic. A random coefficient logit model could add value along this direction (Berry, Levinsohn and Pakes 1995). We will leave this to the future research.

Finally, as we have discussed, our model has only focused on the demand side. In reality, firms could choose market price endogenously. An analysis of the supply side, to explore how firms set price strategically to meet market demand and competition, is necessary. Thus, a full structural model which includes both the demand side and the supply side will work best to fully assess the consequences of outsourcing.

Chapter 3: Assessing the Consequences of Outsourcing: Structural Estimation from the U.S. Airline Industry

3.1 Introduction

In Essay 1, we aim to examine the consequences of outsourcing on a firm's demand. However, there are still some questions unanswered. For example, what is the impact of outsourcing on prices and profits? In this Chapter, we extend the model in the following two ways. First, we allow customers to have different tastes in product characteristics. For example, in practice, leisure passengers may have higher price sensitivity, while business passengers may put more attention on flight flexibility and service quality. Secondly, we propose a structural model to jointly estimate demand and supply. This approach could reveal a firm's profit-maximizing behavior during decision making and make possible the prediction of consequences of future strategic moves based on historical data.

Outsourcing is the common practice of clients employing providers to perform certain activities. Researchers have used various theoretical perspectives to understand outsourcing. Some of the major theories include the transaction cost theory proposed by Williamson (1975, 1985), and the incomplete contract theory advanced by Grossman and Hart (1986) and Hart and Moore (1990). From the transaction cost economics standpoint, outsourcing activities to outside providers rather than internalizing these activities within the firm allows the firm to lower its transaction costs. According to the incomplete contract theory, the risks of opportunism and moral hazard that remain in such incomplete contracts can lower the expected returns. In general, existing theoretical work has agreed that outsourcing can have a direct impact on firms' performance.

However, the empirical evidence in the literature has been unclear (Lafontaine and Slade, 2007). This is mainly due to the fact that outsourcing decisions are typically endogenous. Firms may choose different organizational forms, outsourcing or vertical integration, based on what they expect would promise the best outcome. Such optimizing behavior raises endogeneity issues when assessing the effect of outsourcing on firm performance (Masten, 1993). Previous research in this area use reduced-form models that estimate relationships between outsourcing decisions and firm performance (e.g., Kosová et al., 2012; Forbes and Lederman, 2010; Novak and Stern, 2008). Lucas (1976) argues that it is naïve to predict the outcomes of a firm's future policy changes based on historical data, without considering behavioral changes. Those reduced-form models fail to yield the policy-invariant parameter estimates required to evaluate the consequences prior to outsourcing. Thus, there is a call for structural models to empirically evaluate outsourcing outcomes in the literature (Lafontaine and Slade, 2007). A structural model incorporating both the demand side and the supply side is better suited to capturing the product substitution and the market structure in a market. In addition, a structural model makes it possible to incorporate the endogeneity issues when examining the impact of outsourcing decisions.

The answer to the question, what are the consequences of outsourcing decisions, has remained unclear. However, the answer is crucial for both researchers and practitioners. From the perspective of business practice, executives need to understand whether their own strategic choice of employing outsourcing has been beneficial. Moreover, executives need to learn the outsourcing practices of their competitors, and the resulting consequences of such practices. However, given limited information, it is desirable to predict the post-outsourcing performance using only the information available prior to the outsourcing decision. In this study, we aim to empirically investigate the impact of outsourcing on firm performance, and provide a framework to predict the consequences of such vertical structural changes.

Previous theories have explained that generally firms seek cost reduction and capacity flexibility through outsourcing. However, in addition to an immediate impact on costs, a firm's decision to outsource can have an impact on its future demand, and consequently, its revenue. This maybe especially true for high-customer-contact service industries (e.g., airline industry and hotel industry), because of the characteristics of services: simultaneity of consumption and production, and intangibility and perishability of the service offering (Roth and Menor, 2003). Thus, the performance of an outsourced service providers can directly affect customers' willingness to buy from the client, and even the client's brand reputations in the long run. Therefore, understanding customer preferences is crucial for a firm's "make-or-buy" decision. On one hand, outsourcing may reduce operating costs. On the other hand, service performance of contracted service providers might unfavorably affect the firm's demand.

The airline industry is a good example of high-customer-contact service industry. Vacant seats are perishable and service performance can affect passengers' airline choices. During the past decades, all network carriers have widely contracted with regional airlines on low-density and short routes, because of the cost advantage of regional airlines on those routes. Although regional airlines operates aircraft with higher cost per available seat mile (Forbes and Lederman, 2007), they still maintain cost advantages due to their smaller break-even load factors on limited capacity routes, as well as their lower wage costs.[12]

Moreover, there are different versions of possible vertical relationships between regional airlines and network airlines. For example, regional airlines are mostly independent and provide most of their capacity under capacity purchase agreements (CPAs) with one or more network airlines. However, some regional airlines are (or have been) wholly owned by network carriers. For example, Piedmont Airlines is a fully owned subsidiary of American Airlines. In this study, we empirically investigate the different effects of these two vertical relationships on performance outcomes. Specially, we estimate whether using owned rather than independent regional airlines in a market affects a network airline's performance (e.g., demand, marginal cost, price and profit).

Following Essay 1, we perform an empirical analysis using data from United Airlines (UA) and American Airlines (AA) on duopoly routes from the carriers' common Chicago hub. On those duopoly routes sampled for this paper, UA has outsourced over 29% of capacity to a few independent regionals, while AA insourced over 23% of capacity to its owned regional airline.

[12] Hirsch (2007) finds that United Airlines' senior pilots earn 80 percent more than senior pilots at regional airlines. Senior flight attendants and mechanics earn 32 percent more and 31 percent more than their counterparts at regional airlines, respectively.

In this paper, we propose a structural model under the assumption of profit-maximizing behavior. On the demand side, following Berry, Levinsohn, and Pakes (1995), we assume that heterogeneous customers choose one among the available products in a market to maximize their utilities. Using our sample data, we can estimate demand parameters. On the supply side, a firm strategically sets air fares to maximize its profit, while observing its competitors' strategic choices, its own cost structure and the customer demand in a market. We use the demand estimates from the last step and pricing rules from the supply side model to estimate marginal costs.

Given these demand and cost estimates, we can construct a series of what-if scenarios. Counterfactual analysis based on these scenarios can help firms to predict consequences of outsourcing (e.g., change of price, sales and profit) using information prior to such a strategic move.

The main empirical findings are as follows. First, passengers prefer network airlines' owned regional flights over independent regional flights. It indicates that a network airline, as the ticketing airline, could potentially increase its demand by switching from outsourced independent regionals to fully-owned regional airlines, with other factors held constant. Secondly, owned regional airlines have higher operating marginal costs than do independent regionals. This is, the cost of labor, for example, may be higher for a regional airline that is wholly owned by a network airline, since its employees may demand wages closer to those earned by their counterparts at the network airline (Forbes and Lederman, 2007).

Our analysis in an sample market[13] suggests that (1) American Airlines should outsource the regional route only if the negotiated payment to contracted independent regional airlines would be less than 19.7% of AA's current profit in this market; (2) United Airlines should reverse outsourcing to insourcing only if the current payment to independent regional airlines is more than 14.9% of UA's current profit in this market.

Our study has its contributions in the following aspects. First, this is the first study to adopt a structural modeling approach to account for the endogeneity of the outsourcing decision. Our approach and results could help both researchers and practitioners. While executives have sought cost reduction through outsourcing, they have lacked a workable tool of employing observed data to predict consequences of outsourcing (e.g., impact on price and profit) even before making such a strategic move. Secondly, our results provide empirical evidence on the consequences of outsourcing on a firm's performance. Previous research either has not provided clear answers about the impact of outsourcing on firms' overall performance (e.g., demand and profit) (Kosová et al., 2012), or has only studied outsourcing on firms' indirect performance measures (e.g., operational performance and customer rating) (Forbes and Lederman, 2010; Novak and Stern, 2008).

The rest of this chapter is organized as follows. The following section provides a literature review. Section 3 describes our structural model. Section 4 discusses the estimation procedures. The data are discussed in Section 5. The empirical results are

[13] The sample market is an duopoly market by American Airlines and United Airlines who ticket direct round-trip flights originating from Chicago O'Hare airport to Will Rogers World Airport in Oklahoma City at the 4th quarter in 2009.

presented in Section 6. Section 7 presents and discussed the counterfactual analysis and concluding remarks are offered in Section 8.

3.2 Literature Review

There are at least two areas of literature related to this study. The first area of literature focuses on passenger choice among airlines. The second area is concerned with empirical studies on the impact of outsourcing on firm performance.

3.2.1 Passenger Airline Choices

A main stream of passenger choice research is based on stated preference survey data. The survey data on airline passengers provide detailed information about passenger demographics (e.g., age, gender, income) and trip purpose (e.g., business vs leisure). Studies have found passenger choice depends on airline-specific, passenger-specific, and route-specific characteristics (see, Proussalogou, and Koppelman 1995).

Stated preference data collected by surveys has the advantage of providing detailed information on decision makers (e.g., travel purposes and frequent flyer programs). However, it suffers from strong subjectivity and a risk of response bias. A very limited stream of research on passenger airline choice, like our study, is based on empirical archival data. Some of these papers use Airline Origin and Destination Survey (DB1B) data from the U.S. Department of Transportation in the analysis. For example, Berry (1992) uses a structural discrete choice model to estimate entry in the airline industry. Berry and Jia (2010) use a structural model to estimate the change of passenger preferences and its impact on airline's profitability in the early 2000s.

In addition, passengers may have different preferences even over the same service offering. For example, leisure travelers may place greater emphasis on fares than do business travelers. Most previous research has assumed that passengers are homogenous in order to balance model flexibility and computation complexity. One of exceptions is Berry and Jia (2010) who consider passenger heterogeneity in their structural model and assume that customers can be categorized into two types. This paper is most like our study, although we allow random coefficients for customer preferences. Compared with Berry and Jia (2010), our model allows more flexible and reasonable products substitution pattern (see, Berry 1994).

3.2.2 Outsourcing and Firm Performance

Researchers have used various theoretical perspectives to understand outsourcing. Some main theories include transaction cost theory by Williamson (1975, 1985), and incomplete contract theory by Grossman and Hart (1986) and Hart and Moore (1990). In general, theoretical work predicts that outsourcing can have a direct impact on firm performance.

However, there is no clear empirical evidence in the literature on the impact of outsourcing (Lafontaine and Slade, 2007). It is mainly because outsourcing decisions are endogenous. Firms may choose whether to outsource or not based on the strategy they believe will lead to the best outcome. This optimizing behavior raises endogeneity issues when assessing the effect of outsourcing on firm performance. (Masten, 1993)

Among the empirical studies using revealed preference data, most are industry-based. The findings are mixed. For example, Kosová et al. (2012) use a panel data in the hotel industry and find a very small effect of outsourcing on firm performance (e.g., price and revenue). However, after controlling endogeneity, the effect turns out to be insignificant. Novak and Stern (2008) choose an indirect performance measure, customer ratings of automobile systems. The authors find that integrated firms have higher ratings over long time than do outsourced firms. Forbes and Lederman (2010) also use an indirect performance measure, departure delays of a network airline, and find that a network airline using its own regional airlines has better on-time performance than other airlines using independent regional airlines. Similar to Forbes and Lederman (2010), our study also investigates the impact of using owned and/or independent regional airlines on network airlines. Our study differs from previous research in that: (1) our study uses direct performance measures (e.g., price, cost and profit); (2) our study is based on a structural model rather than a reduced-form model.

In general, out study contributes to two areas of literature. First, we consider customer heterogeneity in airline choices models. Secondly, this study contributes to the outsourcing literature by providing empirical evidence of the effect of outsourcing on a firm's direct performance measure (e.g. price, cost and profitability). Moreover, our study echoes the call for structural analysis in the area.

3.3 Structural Model

In this section, we first introduce the background and foundation of the structural model on both the demand side and the supply side. Then we model customer demand based on a random coefficient logit model, which accounts for both customer heterogeneity and unobserved product factors. On the supply side, we introduce game theoretic models to capture firms' strategic interactions.

3.3.1 Conceptual Model

In practice, firms make optimal decisions to maximize profits. With such considerations, we propose a structural model, as shown in Figure 3.1. On the demand side, understanding how customers make choices is essential to estimating a firm's demand. On the supply side, a firm strategically sets price to maximize its profit, while observing competitors' strategic moves, its own cost structure and customer demand in the market. A structural model incorporating both the demand side and the supply side is better suited to capture product substitutions as well as the market structure. In addition, as discussed earlier, outsourcing decisions are typically endogenous due to the profit-maximizing behavior of firms. A structural model makes it possible to examine the endogeneity issues for outsourcing decisions.

In particular, on the demand side, a discrete choice model is employed to explore customer preferences. We consider several main airline-specific factors in our passenger choice model, e.g., airline fare, service frequency, and on-time performance. In addition, we include an operator type dummy variable that accounts for passengers' preference over different operator types (i.e., mainline flights, owned regional flights or contracted independent regional flights). More detailed variable descriptions are provided in the data section.

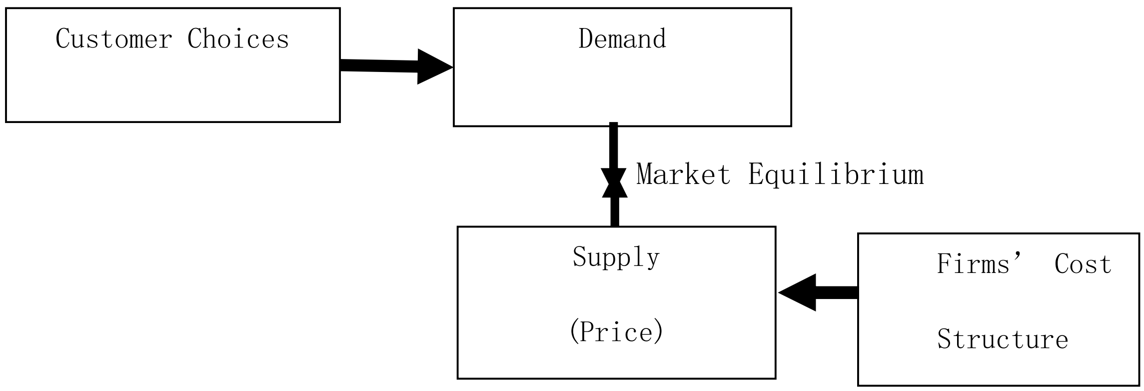

Figure 3.1 A Structural Model

On the supply side, we use game theoretic models to capture the market structure and firms' strategic interactions. We assume a market equilibrium is always reached in each market. The equilibrium can be solved numerically to realize the market price charged and the quantity sold.

Market and Product

Before we introduce the formal modeling, we need to define notions of markets and products based on our data. More details on this will be provided in the following data section.

A market is defined as round-trip direct flights connecting a pair of origin and destination airports. A product (i.e., flight) is defined by the type of operator: network airline, owned regional airline, or independent regional airline. In a market, a firm (i.e., a ticketing airline) chooses one of these three products to serve the market, and sets the price of the product to maximize its profit.

3.3.2 The Demand Model

We adopt a discrete choice model to explore the determinants of customer choice. However, our model differs from standard logit models in the way that we consider customer heterogeneous tastes of products characteristics, and control for unobserved product characteristics. For product j in market k, the utility of a customer i is given by:

$$u_{ijk} = x_{jk}\beta + \alpha_i p_{jk} + \eta_{jk} + \xi_{ijk}, \qquad (1)$$

where

- x_{jk} is a vector of product characteristics,
- β is a vector of the customer i's tastes of product characteristics,
- α_i is the price sensitivity of the customer i,
- p_{jk} is the price of product j in market k,
- η_{jk} is the unobserved (to researchers) characteristics of product j in market k,
- ξ_{ijk} is an i.i.d. (across products and customers) "logit error".

Here, we assume that customers have heterogeneous preferences over product characteristics. Ideally, tastes of all characteristics could be different across customers. However, that requires a very large set of data points. Due to data limitations, in this model, we only let α_i be a random coefficient to capture different customers' price sensitivity, while keeping other dimensions of customer taste, that is, β, to be constant across customers. In particular, following Berry et al. (1995) (BLP), we assume that α_i are i.i.d. normal distributed across customers.

The term η_{jk} captures unobserved factors (to researchers) that affect customer choices. For example, ticket restrictions, time of departure, and membership in an airline's frequent flier program, all could affect passenger choices. Because these factors are observable to the passenger, they may influence his/her choice. However, because they are unobservable to the researcher, they will contribute to the errors in the model. Furthermore, the unobserved product characteristic η_{jk} is likely to be correlated with price. For example, tickets with different restrictions may have systematically different prices. This kind of correlation leads to endogeneity concerns.

In MNL models, adding a constant to every utility value does not change choice probabilities (Ben-Akiva and Lerman, 1985). To make the choice model uniquely identifiable, we have to set an outside option as a reference level. Following BLP (1995), the utility of the outside option is given by the following equation:

$$u_{i0k} = \xi_{i0k}, \qquad (2)$$

where ξ_{i0k} is also a "logit error" in the model.

Define the mean utility of product j in market k as

$$\delta_{jk} = x_{jk}\beta + \eta_{jk}. \qquad (3)$$

We can rewrite the utility of product j in market k for customer i as

$$u_{ijk} = \delta_{jk} + \alpha_i p_{jk} + \xi_{ijk}. \qquad (4)$$

Thus the market share of product j in market k is given by

$$S_{jk}\left(\beta,\alpha\right) = \int \frac{\exp\left(\delta_{jk} + \alpha_i p_{jk}\right)}{1 + \sum_{m=1}^{J} \exp\left(\delta_{mk} + \alpha_i p_{mk}\right)} dF\left(\alpha\right), \qquad j = 1, \ldots, J \qquad (5)$$

where J is the total number of products in the market, and $F\left(\alpha\right)$ is the density function of the normal distribution of random coefficient α_i. Notice that $S_{jk}\left(\beta,\alpha\right)$ is a function of demand parameters $\left(\beta,\alpha\right)$ that are to be estimated. In the real world, the market shares of different products, $\widetilde{S_{jk}}$, are observed. Therefore, the demand side parameters can be estimated by making the calculated market shares, as given in Equation (5), as close to observed market shares as possible. That is, $S_{jk}\left(\beta,\alpha\right) = \widetilde{S_{jk}}$.

3.3.3 The Supply Model

We use a game theoretic model to capture firms' strategic interactions in a market. In reality, there are a variety of horizontal and vertical interactions among ticketing airlines and operating airlines. For example, a ticketing airline would need to negotiate outsourcing contracts with independent regionals. Since principals and agents do not always have incentives that are aligned, this causes the well-known double marginalization problem. In our game, we simplify the vertical interaction and assume that outsourced regionals provide the service at their marginal costs. The reasons for this are as assumption follows. First, with current available data, we never observe how much a ticketing airline pays for services provided by independent regional airlines. Therefore, it makes it impossible to estimate the costs of ticketing and the cost of operating airlines separately in a game. Secondly, as discussed in section 2 in Essay 1, most contracted regionals provide services to a network airline under capacity purchase agreements. Under these agreements, only network airlines get to decide ticketing prices, and they pay a fixed amount to buy capacity from regional airlines. In summary, we assume that network airlines are the only decision makers in the game.

In addition, we assume prices are set according to a static Nash equilibrium in the market. Define a firm l 's total profit in market k as

$$\Pi_{lk} = \sum_{j \in S_{lk}} \left(p_{jk} - c_{jk} \right) Q_{jk}, \qquad (6)$$

where c_{jk} is the marginal cost of product j and Q_{jk} is the quantity sold of product j in market k. S_{lk} indicates the whole set of products offered by firm l in market k.

We further assume that a ticketing airline maximize its profit in each market separately. The first order conditions are

$$\frac{\partial \Pi_{lk}}{\partial p_{jk}} = Q_{jk} + \sum_{h \in S_{lk}} \left(p_{hk} - c_{hk} \right) \frac{\partial Q_{hk}}{\partial p_{jk}} = 0 \qquad \forall j \in S_{lk}. \qquad (7)$$

Solving the first order conditions, we can write the equilibrium price-cost margins for firm l in matrix from as:

$$PCM_k^l = p_k - c_k = -\left(T \bullet \Delta \right)^{-1} Q_k, \qquad (8)$$

where Δ is a matrix of market response to price. And

$$\Delta\left(i, j\right) = \frac{\partial Q_{jk}}{\partial p_{ik}} \qquad \forall i, j \in S_k. \qquad (9)$$

T is given by

$$T = \begin{cases} 1 & \forall i, j \in S_k \\ 0 & \text{otherwise.} \end{cases} \qquad (10)$$

3.4 Estimation

We estimate the structural model in two steps. We first estimate the demand model following the procedures of BLP (1995) and Nevo (2000). Armed with demand estimates, we can estimate marginal cost for the supply model. In the next step, we regress the estimated marginal costs on cost factors to estimate cost parameters. Following this approach, the demand estimates are consistent and efficient, while the cost estimates are inefficient but still consistent.

3.4.1 Demand Model Estimation

Our random coefficient logit model makes it possible to account for unobserved product factors and customer heterogeneity, which is not possible in a simple logit model. These benefits are at the expense of added computational complexity. For example, there is no closed-form solution to calculate market shares from Equation (5).

In particular, we use procedures as described in Nevo (2000) and implement them in MATLAB R2014b. First, we estimate mean utility δ_{jk} numerically by making observed market shares with estimated market shares as close as possible. This is the "contraction mapping" approach as stated in BLP (1995). Second, we regress the estimated mean utility on the demand characteristics to get estimates of coefficients. To account for the price endogeneity issues, instrumental variables are required to estimate demand parameters by using a generalized method of moments (GMM) estimation. The choice of these instruments for the demand model will be discussed in detail in the next data section.

3.4.2 Supply Model Estimation

We first assume that marginal cost function is given by:

$$c_{jk} = w_{jk}\phi + \omega_{jk}, \qquad (11)$$

where

- w_{jk} is a vector of observed cost factors of product j in market k,
- ϕ is a vector of cost parameters to be estimated, and
- ω_{jk} is a vector of unobserved cost error.

From estimated demand model parameters, we can estimate price-cost margin $\widehat{PCM}$ by Equation (8). We can then calculate the estimated marginal cost as

$$\widehat{c_{jk}} = p_{jk} - \widehat{PCM_{jk}} \qquad (12)$$

We then use the estimated marginal cost to estimate cost parameters ϕ from a set of linear system equations given by Equation (11).

3.5 Data

The market, product definition and most variables have been discussed in great detail in Chapter 2.5. Here we only introduce new variables used in the current model.

3.5.1 Variables

Demand Variables

To control the differences across markets, we include *Distance* (i.e., the direct distance between the origin and the destination) to capture the variability of passengers' mean utility. Secondly, *Distance2*, square of distance, is included to capture potential U-shaped air-travel demand (Berry and Jia, 2010). The rationale behind is that flights compete with trains and cars on short routes; as distance increases, the demand for flights in general would increase at first, but decreases later on when travel distance increases beyond an inflection point. Thirdly, we construct *PassPerFlight*, the average number of passengers per flight, as a proxy for passengers' preferences for larger-size jets over small-size jets. Truitt and Haynes (1994) find that passengers prefer full-size jets over smaller regional jets.

Cost Variables

We construct additional variables to measure exogenous marginal cost shifts as follows. First, a dummy variable, *Slot_control*, is set of 1 for a slot-controlled destination airport, and 0 otherwise. Higher landing fees due to the slot controls may result in higher marginal costs. Four airports are under slot control in our sample: LaGuardia, Kennedy and Newark in New York, and National in Washington, DC.

Secondly, a dummy variable, *Hub*, is set of 1 if the destination airport is a hub for a ticketing airline, and 0 otherwise. Marginal costs may be lower due to denser traffic (Berry et al., 2006) , and a market ending with hubs at both end points (Chicago O'Hare being a hub for both American Airline and United Airline) would normally have denser traffic. Finally, some cost variables are already defined above on the demand side. For example, different operators, indicated by operator type dummy, *Owned_regional*, *Indep_regional* and *Network*, may have different operating costs.

3.5.2 Data Summary

Summary statistics on variables, grouped by ticketing airlines, are provided in Table 3.1.

Table 3.1 Summary Statistics for Main Data

	AA		UA	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Fare ($100)	1.522	0.327	1.562	0.315
Frequency (No. of flights per day)	6.323	4.083	6.624	4.298
Distance (100 miles)	7.802	2.323	7.802	2.323
ArrDelay (min. per flight)	11.929	7.517	12.167	9.022
ArrDelay1 (min. per flight)	17.547	6.190	18.205	8.010
PerDelay (%)	26.554	7.868	25.815	8.117
Cancel	0.029	0.024	0.024	0.025
Owned_regional	0.238	0.426		
Indep_regional			0.292	0.455
PassPerFlight	22.769	14.971	24.241	18.153
Slot_control	0.129	0.336	0.129	0.336
Hub	0.025	0.156	0.113	0.317
Observations	240		240	

From Table 3.1, AA has slightly lower average fares and lower flight frequencies compared to UA. We note that the average delay time for AA is less than that for UA. However, compared with UA, AA has a higher percentage of flights that are more than 15 minutes late and a higher percentage of cancelled flights. In general there is no clear sign as to which airline has better on-time performance. Approximately 24% of routes are served by owned regional operators, and 29% by independent regional airlines in our sample. Pearson correlation coefficients are calculated and shown in Table 3.2.

Table 3.2 Pearson Correlations

	Fare	Frequency	Distance	PerDelay	ArrDelay	ArrDelay1	Cancel	Owned_ regional	Indpep_ regional
Fare	1								
Frequency	0.222*	1							
Distance	0.343*	-0.070	1						
PerDelay	0.039	0.093	0.074	1					
ArrDelay	0.006	0.098	0.059	0.932*	1				
ArrDelay1	0.046	0.115	0.089	0.903*	0.979*	1			
Cancel	0.151	0.327*	-0.276	0.297*	0.272*	0.288*	1		
Owned_ regional	0.113	-0.148*	-0.396*	0.109	0.040	-0.029	0.133*	1	
Indept_ regional	-0.014	-0.381*	-0.313*	-0.063	-0.043	0.013	0.073	-0.152	1

*. Correlation is significant at the 0.01 level (2-tailed)

In Table 3.2, *PerDelay*, *ArrDelay* and *ArrDelay1* are all highly correlated (over 0.9), indicating that these three on-time performance measures are consistent. Another on-time performance measure in our data, *cancel*, appears not to be consistent with other performance measures (below 0.3). *Indep_regional* is negatively correlated with *Frequency* (-0.381), which is consistent with the observation that regional airlines operate routes with fewer flights per day than do network carriers. Moreover, both *Owned_regional* and *Indep_regional* are negatively correlated with Distance (0.3~0.4), which is consistent with the observation that regional airlines serve shorter routes compared with their network carrier counterparts. Previous research has found that vertically integrated regional airlines have better operational performance (e.g., on-time performance) (Forbes and Lederman, 2009; Forbes and Lederman, 2010). In our data, there is no clear evidence that regionals and on-time performance are correlated in any direction, except for *Owned_regional* and *cancel* (slightly above 0.1).

3.5.3 Instruments for the Demand

Price Instruments

Given that prices are endogenous in the estimation of demand, we need instrumental variables to identify the fare coefficients. One common strategy is to explore the rival product attributes and the competitiveness of the market. However, under our settings, only two airlines compete in each duopoly market. Therefore, it is infeasible to extract such instruments in this way. Another strategy is to follow Nevo (2000) to examine the panel structure of the data. It is suggested that prices of a brand in other markets could be valid instruments. Prices of brand j from a given firm in other markets will be correlated with the price in a market due to the common marginal cost, but unlikely to be correlated with the market-specific valuation of the product due to the unobserved characteristics in this market. Therefore, these prices in other markets could potentially serve as valid instruments. Similarly, we choose the average fare per mile, *FarePerDistAvg*, over all other routes for a ticketing airline as an instrument for its fare on a given route. These are our first category of instrumental variables, the so-called "Hausman" instruments. With the reservation that there still could be some situations when the independence assumption might not hold, as discussed in Nevo (2000), we run estimations over each of these instrumental variables and keep those that provide us reasonable results.

The second category of instrumental variables are those that affect costs but not the demand. *Hub* is a dummy variable indicating whether the destination is a hub for the ticketing carrier. For example, for flights from Chicago to Washington Dulles, this variable is coded 1 for UA and 0 for AA, since Dulles is a UA hub but not an AA hub. On routes with denser traffic, larger planes might be used, which will in turn affect the marginal cost (per passenger) of a flight. As a robustness check, we estimated the model with and without these instruments. There is no significant difference between the estimated parameters.

The third category of instruments, *Fare_Fit*, include the fitted values of fare after regressing the fare over the characteristics of the destination cities. The exogenous variables in the regression are: carrier dummies, route level characteristics (e.g., distance and whether the destination is a tourist city), population size as market size. The fitted fare instruments are finally discarded due to collinearity concerns.

Frequency Instruments

The instruments for frequency, *Fq_Fit*, are constructed as the fitted frequency over the characteristics of the destination cities.

We include the interaction and second order term of the above variables as long as there is no collinearity problem. Other exogenous variables in the demand function are also included in our estimation. The instruments that we finally adopt are summarized in Table 3.3.

Table 3.3 Summary Statistics for Instruments

	Mean	Std. Dev.	Min	Max
FarePerDistAvg ($1/mile)	0.266	0.017	0.221	0.309
Fare_Fit ($100)	1.580	0.191	1.131	1.837
Fq_Fit (No. of flights per day)	6.410	3.474	1.340	15.574
Hub	0.1125	0.316	0	1
Observations	480			

3.6 Empirical Results

We first report the demand-side estimates from our random coefficient logit model. Based on these results, we estimate marginal cost in each market, which then allows us to estimate the parameters for marginal cost factors.

3.6.1 The Demand Model

In Essay 1, a logit model is our approach. Here we extend our estimation with a random coefficient logit model. To demonstrate the advantages of incorporating customer heterogeneity into our estimation, we compare our demand model (M1) with a simple logit model (M0) which does not account for unobserved customer heterogeneity. In both Models, we use *ArrDelay1*[14] as the on-time performance measure. The estimation results are summarized in Table 3.4.

In M1, as discussed earlier, we allow a random coefficient for customer price preferences. Note that the difference between the random coefficient model and the simple logit model are in both the mean effects, and the allowance for systematic heterogeneity among customers. We find that accounting for customer heterogeneity makes a significant difference in our results. The mean price sensitivity based on the logit model M0 is -1.311, while, under the random coefficient model, M1, the sensitivity is -2.460, a 47% difference in the product's self-elasticity. These findings are consistent with the pioneering work in the econometrics field by BLP (1995).

Most other estimated parameters from M0 and M1 are consistent, except for the operator-type dummy coefficients. They shift down systematically for both owned regional airlines (-0.318 in M0 vs. -0.507 in M1) and independent regional airlines (-0.489 in M0 vs. -0.655 in M1). This is because the random coefficient model allows for a subgroup of customers who strongly prefer regional flights, as well as another subgroup of customers who strongly prefer network airlines (i.e. the reference dummy variable is zero).

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[14] In the following robust tests, we used different on-time performance measures, *ArrDelay*, *PerDelay*, and *Cancel*. None of these change our main findings, similar as the robust test results in Essay 1.

Table 3.4 Demand Estimation of M0 and M1

	M0		M1	
	DV: Logit		DV: Market Share	
	Coefficient	Std. Error	Coefficient	Std. Error
(Constant)	**-8.795***	0.195	**-5.550***	0.312
Fare	**-1.311***	0.254	**-2.460***	0.553
Fare_SD			**0.864***	0.138
Frequency	**0.099***	0.009	**0.105***	0.012
Distance	**0.276***	0.082	**0.244***	0.094
Distance2	**-0.010***	0.004	**-0.009***	0.004
PassPerFlight	**0.008***	0.001	**0.013***	0.002
Owned_regional	**-0.318***	0.121	**-0.507***	0.173
Indep_regional	**-0.489***	0.103	**-0.655***	0.152
AA	**-0.157***	0.024	**-0.160***	0.042
ArrDelay1	-0.002	0.002	-0.005	0.003
R-square	0.809			
GMM criterion function			6.880E-18	

*Significant at the 0.05 level

On the other hand, the logit model is restricted to an average (mean) effect. This restriction also explains why the constant in M0 (-8.795) has a much larger absolute value than that in M1 (-5.550). Much of the unobserved heterogeneity has to be explained by the constant in the simple logit model.

After demonstrating the importance of accounting for customer heterogeneity with our airline industry settings, we focus on the estimates of our random coefficient logit model M1. First, the mean coefficient of *Fare* is significantly negative (-2.460) and heterogeneous (*Fare_SD* = 0.864, significant at 5%)[15]. This indicates that customers have different price sensitivities. Secondly, the estimated coefficient for *Frequency* is significant and positive as expected. Thirdly, the estimated coefficient for *Distance* is positive and significant, while the coefficient for *Distance2*, is significantly negative. These results are consistent with previous research that air-travel demand is U-shaped (Berry and Jia, 2010). Fourthly, the estimated coefficient for *PassPerFlight* is significantly positive, suggesting that customers prefer larger-size flights as expected.

Further results from M1 show that the estimate for *AA* is negative and significant, indicating that UA has a better branding effect on the routes being investigated. Both estimates of *Owned_regional* and *Indep_regional* are significant and negative. Since the reference dummy for operator type is *Network*, this supports our hypothesis that passengers prefer network flights over regional airline flights. Furthermore, consistent with our previous finding in Essay 1, passengers prefer owned regional flights over independent regional flights (-0.507 vs. -0.655). A t-test indicates that the mean difference between these coefficients is significant. In addition, we did not find any significant effect of on-time performance on passenger

[15] That is, the price sensitivity follows a normal distribution with a mean of -2.460 and a standard deviation of 0.864.

choice. As discussed in the literature review section in Essay 1, researchers have not agreed on the effect of on-time performance on passenger choice with mixed findings reported.

In practice, passengers are unlikely to know whether a flight is operated by an owned or independent regional airline. Therefore, a key question is why passengers may prefer owned regionals over outsourced independent regional airlines in our sample markets. The underlying reasons may be as follows: First, owned regionals have incentives to better coordinate with their network partners than do independent regionals (Forbes and Lederman, 2007). Thus, vertically integrated airlines may have potentially better operational performance and service quality than independent regionals (Forbes and Lederman, 2010). Consequently, passengers may prefer owned regionals over independent regionals. Secondly, it may be argued that in our sample, American Eagle is the only owned regional, and, therefore, our results may be due to specific airline attributes. However, in our model, we control for regional airlines' firm level factors; e.g., fare, flight frequency. In addition, we have a fixed effect at the (ticketing) airline level to control for carrier-specific factors that may be influencing passenger choice.

In general, our demand estimates are in line with the results derived in Essay 1 using a simple logit model without considering customer heterogeneity. However, the random coefficient logit model has more flexibility to capture unobserved customer heterogeneity as well as the market substitution patterns, as discussed above. The consistency also indicates that our estimation results under random coefficient logit model are robust.

3.6.2 The Supply Model

As discussed earlier, given the demand estimates, we can estimate marginal cost in a market. Then a set of linear systematic equations are used to regress marginal cost on all exogenous cost factors. In particular, the dependent variable is marginal cost divided by distance (i.e., marginal cost per passenger mile). Table 3.5 summarizes the results of the cost-side estimation.

We first control the time effect in each quarter as a fixed effect, as shown in the left half of Table 3.5. First, the estimated constant, i.e., marginal cost per passenger mile, is equal to 0.136 and significant at the 0.05 level. We compare our results with airlines' reported operating costs per available seat mile in Form 41 provided by the Department of Transportation[16]. The average reported operating cost in 2006 was 11.4 cents. Our estimated mean marginal cost per passenger mile is around 13.6 cents, a figure reasonably close to the reported operating cost.

Secondly, the estimated parameter of *Owned_regional* is significant and positive (0.030). Note that the reference dummy of operator type is *Indep_regional* in the cost model. Our finding indicates that owned regional airlines have higher operating costs than those of independent regionals. This is consistent with what we have discussed in the section 2 of Essay 1. For example, when a regional airline is wholly owned by a network airline, regional employees may demand wages closer to that earned by their counterparts at the network airline (Forbes and Lederman, 2007). In addition, the estimated parameter for *Network* is significantly negative (-0.047), indicating that network airlines have lower operating costs per passenger mile

[16] Available at http://www.transtats.bts.gov/Fields.asp?Table_ID=290.

compared with both owned and independent regionals. Our findings are consistent with Forbes and Lederman (2007), where they point out that regional jets normally operated by regional airlines may have higher costs per available seat mile than full-sized jets operated by network airlines.

Further results show that the marginal cost of ticketing airline AA (with a significant negative estimated parameter, *AA*=-0.008) is slightly lower than that of UA. In addition, the estimated parameter for *Slot-control* is positive and significant (0.038). Costs are probably higher in slot controlled airports due to higher landing fees and greater congestion. Moreover, the estimate for *Hub* is insignificant.

Table 3.5 Cost Estimation Results

	Time fix effect		Time random effect	
	DV: Marginal Cost /distance		DV: Marginal cost/ distance	
	Coefficient	Std. Error	Coefficient	Std. Error
(Constant)	**0.136***	0.004	**0.134***	0.004
Owned_regional	**0.030***	0.007	**0.031***	0.007
Network	**-0.047***	0.004	**-0.044***	0.005
AA	**-0.008***	0.003	**-0.008***	0.003
Slot_control	**0.038***	0.005	**0.039***	0.005
Hub	0.006	0.005	0.007	0.006
R-square	0.3837			0.3843

*Significant at the 0.05 level

We then test another model with a random time effects assumption. The results are summarized in the right half of Table 3.5. All the estimation results are consistent with the above fixed time effects model.

3.7 Counterfactual Analysis

Armed with our demand and cost estimates, we investigate the potential consequences of outsourcing regional flights by a ticketing airline in a market. Using a structural approach allows us to perform policy simulation to evaluate a prospective outsourcing practice. In addition, based on the results of both demand and cost analyses, we argue that outsourcing to independent regional airlines could decrease the ticketing airlines' demand, while independent regional airlines may have a lower marginal cost compared to owned regional airlines. Therefore, we aim to examine the potential tradeoff that a network airline may take when employing an outsourcing strategy.

In particular, our analysis follows these procedures. First, based on the estimated demand function and cost structure, we calculate the equilibrium price, sales, and profit for all ticketing network airlines (i.e., profit maximizers) in each market. This develops a base scenario. We then calculate the equilibrium price, sales, and profit for each ticketing network airline under a series of what-if scenarios (e.g., employing an outscoring practice), and compare the outcomes to the base case.

Base Case

We pick the following sample market from our data: passengers taking direct round-trip flights originating from Chicago O'Hare airport to Will Rogers World Airport in Oklahoma City at the 4th quarter in 2009. AA and UA as ticketing airlines almost equally shared the market. UA used independent regional airlines to operate in the market, while AA used its owned regional. This is the base case.

Scenario 1: Outsourcing Case

If AA plans to outsource to independent regional airlines as new operators to replace its owned regional, while UA keep unchanged, we can use the scenario analysis to predict the impact on both airlines' performance, e.g., price, cost and profit. The simulation results based on our structural model are summarized in Table 3.6.

First, as discussed earlier, replacing owned regional airlines with independent regional airlines decreases marginal cost. That is why our analysis reports that AA could decrease its marginal cost per passenger significantly, even though prior to outsourcing, AA has a cost disadvantage compared to UA.

Secondly, with a lower marginal cost than UA after outsourcing, AA has an incentive to cut its average price from 397.2 dollars per passenger to 328.7 dollars per passenger (round-trip) in the market. Faced with the aggressive price cutting from its competitor, UA has no choice, but to cut price as well.

Thirdly, even though customers prefer owned regionals over independent regionals, customers would benefit from the price cutting by both ticketing airlines after AA's outsourcing. This would drive up the total market demand. In addition, both firms benefit as well and their revenues increase.

In summary, based on our analysis, AA is expected to improve its profit on this route 19.7% by moving to outsourcing. As discussed earlier, under "capacity purchase agreements" (CPA), AA retains all ticketing revenue and pays a fixed amount to buy independent regionals' service capacity. Therefore, AA should outsource to independent regionals only if the fixed payment is less than 19.7% of its current profit in this market.

Scenario 2: Insourcing Case

If UA plans to reverse outsourcing and replaces outsourced independent regional airlines with an owned regional airline, and AA keeps unchanged, we can use the scenario analysis to predict the impact on both airlines' performance. The simulation results are also summarized in Table 3.6.

First, replacing independent regional airlines with an owned regional airline increases marginal cost. Our results suggest that UA have higher marginal cost than AA after insourcing.

Secondly, with higher marginal cost, UA is expected to increase its average price from 367.9 dollars per passenger to 395.6 dollars per passenger (round-trip) in the market. On the contrary, AA is expected to decrease its average price due to cost advantages over UA.

Thirdly, passenger enplanements for UA, therefore, decrease over 7%, while those for AA increase over 19%.

In summary, UA's profit on this route is expected to decrease 14.9% by moving from outsourcing to insourcing. However, if under current capacity purchase agreements, UA pays the fixed amount greater than 14.9% of its current profit in the market to independent regionals, UA still has incentive to reverse outsourcing.

Table 3.6 Counterfactual Analysis Results

Scenario	Ticketing Airline	Price ($)	Sales (# of passengers)	Marginal cost ($)	Revenue ($)	Profit ($)
Base case	AA	397.2	1520	216.8	603,774	274,208
	UA	367.9	2000	200.5	735,800	334,800
Outsourcing case	AA	328.7	2139	175.2	703,089	328,337
	UA	354	2190	200.5	775,260	336,165
Insourcing case	AA	370.2	1812	216.8	670,802	277,961
	UA	395.6	1855	242.1	733,838	284,743

Our results have direct and important managerial implications. In 2012, American Airlines Group (parent company of American Airlines) announced a plan to gradually outsource more of its regional business, previously operated by its owned regional, American Eagle, to independent regionals, in an effort to restore profitability (Cameron and Incas, 2012). The results of our policy simulation appear to provide support for American Airlines Group's outsourcing strategy. In general, our model provides firms with a tool to evaluate potential consequences even before making a policy change, e.g., outsourcing and insourcing.

3.8 Conclusions

The central question this study aims to answer is how one can assess the consequences of outsourcing, given endogeneity issues embedded in firms' profit-maximizing decision-making. We try to answer this question for a specific context: network airlines' outsourcing to independent regional airlines in the U.S. airline industry. This is the first study to model and estimate the equilibrium effects of outsourcing. Previous research have used reduced-form models. Lucas (1976) argues that it is naïve to predict the outcomes of future firms' policy changes based on only historical data by using reduced-form models. Thus, there is a call for structural models to empirically evaluate outsourcing outcomes (Lafontaine and Slade, 2007). Our study fills the exact gap.

Our proposed procedure is useful for both researchers and practitioners. The counterfactual analysis can be used to calculate many impacts, such as the potential effects on prices, market shares and profits, before employing an outsourcing.

While our results are promising, considerably more research could be implemented in future. First, our demand model accounts for customer heterogeneity only for price sensitivity due to data limitations. If more customer-level data are available, e.g., individual demographical data, this could help to explore different tastes in both price and other product attributes across customers.

Secondly, we model a supply-side game by assuming that there exists only horizontal interactions among firms, since the transaction fees between outsourcers and service providers are inaccessible. A full game considering both horizontal interactions and vertical interactions would provide more interesting insights on firms' behavior and decisions. We will leave this to future research.

Chapter 4: Estimating Choice Models with Censored Sales Data in Revenue Management

4.1 Introduction

4.1.1 Motivation and Research Objectives

Following its successful application in the airline industry, revenue management (RM) has been applied in a wide range of service industries, such as hotels, car rentals, and restaurants. Revenue management systems are designed to maximize the revenue take of firms by accounting for the specific needs and characteristics of the customer base. An important assumption of traditional RM is that customer demands for different fare classes are independent. For example, it is normally assumed that a customer interested in a certain fare class would never buy tickets from other fare classes, even when tickets in the preferred class are sold out.

Over the years, both researchers and practitioners have challenged this unrealistic assumption (Boyd, 2004; Talluri and van Ryzin, 2004). It is reasonable to assume that many customers who cannot find their preferred type of ticket, will choose to purchase their next best available alternative. Researchers have called for including a customer choice framework into traditional RM models that allows a customer to purchase any available product, providing for the highest utility. A number of theoretical papers have been written that incorporate optimization algorithms in this new area: choice-based RM (e.g., Talluri and van Ryzin, 2004; Zhang and Cooper, 2006). In addition, empirical research has demonstrated that transforming from traditional RM to choice-based RM systems could increase a firm's revenues by 1~5% (Vulcano et al., 2010).

However, before any choice-based RM algorithm can be implemented in practice, it is necessary to accurately estimate customer choice parameters from available sales data. This task is challenging because in the revenue management setting, generally only the sales data for the focus firm are observed, while other competitors' sales data are generally not accessible. This is an issue since the general discrete choice model setting requires that all choice alternatives are observed. Therefore, traditional estimation methods cannot be directly applied. Thus, the call for new methods to jointly estimate choice parameters and customer choice when market sales are not completely observed.

The majority of existing choice-based methods follow a finite-period setting where customers arrive randomly within a finite number of time periods. For example, Talluri and van Ryzin (2004) divide the sales time into discrete intervals and assume that there is at most one customer in each interval. This Poisson-type demand assumption is convenient in order to maintain a tractable model. However, there are two significant drawbacks: (1) in most revenue management industries, observed sales data have a much higher variability than that in a Poisson demand distribution[17]; (2) the size of discrete time intervals will highly affect the final estimation results, and are arbitrarily determined.

In light of these issues, Newman et al. (2014) develop a two-step procedure to simplify the estimation of customer parameters. However, they also assume that

[17] Talluli (2009) points out that in most revenue management industries, a coefficient of variation (CV) is 2 or 3 compared with 1 in the demand distribution as in Talluri and van Ryzin (2004).

demand follows a Poisson distribution. In section 4, our results demonstrate that models, such as the procedure in Newman et al. (2014) may result in unreliable and biased estimates, especially when the real demand distribution is significantly different from the assumed distribution.

Using a different approach, Talluri (2009) introduces a finite-population procedure that allows for an arbitrary demand distribution. This work is most relevant to our approach since both the Talluri (2009) method and the approach used in this dissertation are free from demand distribution assumptions. Talluri (2009) proposes a heuristic approach to estimate choice parameters first, and these parameters are then used to estimate population size. However, the approach requires information with regard to sales rates for numerous pairs of time periods, which makes the implementation of the algorithm difficult to use, in practice.

We propose a new parameter estimation methodology that overcomes the above drawbacks. We adopt a two-part procedure. The first part is a conditional likelihood estimation of customer choice parameters based on all observed purchases. We then reformulate the second part into an adjusted case-control sampling problem as in Lancaster and Imbens (1996). No-purchase (potential) customers are never observed in most revenue management datasets. In order to account for this situation, we randomly draw a sufficiently large sample size of “pseudo-no-purchase” data to impute the missing data. Details are discussed in Section 3. Finally, we estimate the second-part of the model with missing data using the Expectation-Maximization (EM) algorithm (Dempster et al., 1977).

Simulation based on industry hotel data demonstrates that the estimation error of Newman et al. (2014) may be as high as 16% (even up to 50% under some conditions), especially when the true demand is far from the assumed Poisson distribution. Previous research reports that the performance of a choice-based revenue system depends on the estimation accuracy of parameter estimates. For example, Vulcano et al. (2010) find that even a 10%~25% estimation error may completely deteriorate the revenue improvement of implementing a choice-based system. Therefore, the misspecification of demand distribution may be dangerous for estimation methods contingent on a demand distribution. On the contrary, simulation results show that our method ensures consistent and unbiased estimates under most conditions. The estimation accuracy of our method is within a reasonable range and dominates that of Newman et al. (2014), especially when true demand has high variability.

4.1.2 Contributions

The main contributions in this paper are:

- This is the first paper to point out that the performance of methods contingent on demand distribution assumptions are very sensitive to their distribution specifications. Any deviation from the true demand distribution may result in unreliable and biased estimates. This important point has been overlooked in prior research. In practice, researchers and practitioners should be very cautious when implementing distribution-based methods when there is not sufficient information about the true demand.

- We propose a new estimation methodology which allows for arbitrary demand distributions and requires no exogenous demand information. Our method is the first that can be implemented with most revenue management datasets that are not contingent upon any prior knowledge about demand processes.
- Our estimation procedure includes price and other product attribute variables, which make it possible for practitioners and researchers to understand customers' willingness to pay. Since most existing choice-based optimization algorithms do not have price decision variable, our method can serve as inputs into advanced algorithms for product availability and price optimization.

4.1.3 Outline

The remainder of the chapter is organized as follows: In section 2 we conduct a literature review. In section 3 we propose our model and discuss related estimation issues. Section 4 describes a simulation test to identify problems in existing estimation methods and compare estimation performance with our method. In section 5 we discuss the managerial applications of our results. Finally, section 6 summarizes our findings and proposes directions for future research.

The sample *R* codes for generating synthetic data and fitting estimation models are provided in the Appendix.

4.2 Literature Review

Estimation of customer choice preference over available products (e.g., customer's price sensitivity) in revenue management field is essentially a discrete choice problem to estimate the parameter of an alternative, which is completely censored since the purchasing data from competitors are never observed. This problem is not unique to the revenue management area. For example, choice models have been widely used in marketing and economics to model purchase probabilities. When faced with similarly censored demands, researchers generally disregard the censored problem and assume the potential market size to be exogenously given; for example, in the marketing literature, Besanko et al. (1998) and Nevo (2001). A good review of methods for both choice-based and non-choice-based models can be found in Vulcano et al. (2012). In addition, Weatherford and Ratliff (2010) provide a general review for choice-based models in the revenue management field.

The main stream of research for choice-based models in the revenue management field has focused on finite-period methods. These procedures model sales processes as random customer arrivals within a finite number of time periods. Talluri and van Ryzin (2004) divide the total sales time into discrete intervals and assume at most one customer in each interval. In their choice model, price is the only product attribute. A major drawback with their method is that there is no rule to determine the length of a time slice. Subsequent research (Newman et al., 2014; Talluri, 2009) notes that the discretization of time causes a bias in estimation since the estimates depends on the length of a time slice. Vulcano et al. (2010) later investigated the application of the algorithm proposed by Talluri and van Ryzin (2004), but reported some counter-intuitive findings. Talluri and van Ryzin (2004) also rely on an Expectation-Maximization (EM) algorithm (Dempster et al., 1977) to perform their estimation because no-purchase customers are never observed.

Later research has focused on simplifying the estimation process in Talluri and van Ryzin (2004). One steam of research adopts a nonparametric approach to model customer utility, (e.g., van Ryzin and Vulcano (2013), Haensel and Koole (2011), Farias et al. (2013) and Vulcano et al. (2012)). In their simplified model settings, the customer decides to make a choice or purchase depending on the customer's rankings of products; that is, prices and other product attributes do not have a direct impact in this kind of choice models. Therefore, their estimation results cannot help practitioners understand the relationship between customer choice and product attributes; e.g., price. Moreover, this is obviously problematic because the model neglects the critical fact that prices change dramatically in real revenue management industries and that customers are very sensitive to price changes.

Another group of researchers have sought to simplify the estimation procedures by considering a conditional-likelihood-based approach. Ratliff et al. (2008) propose a two-step estimation procedure in which the estimation problem was decomposed into two stages based on conditional and marginal likelihoods, respectively. However, the authors assume market size to be exogenously given and omit the risk of biased estimations due to unobserved purchasing data. Newman et al. (2014) further develop an estimation routine based on a similar two-stage approach, requiring no exogenous market information. Their method significantly improves computational efficiency compared to Talluri and van Ryzin (2004). Nevertheless, their work also relies on the strong assumption of Poisson-distributed arrivals of customers.

The only exception in the existing literature is the finite-population approach by Talluri (2009). The author proposes a method calculating risk-ratios between any pair of time intervals with the same arrival rate. A risk-ratio approach makes it possible to move from a challenging joint estimation problem to a single variable estimation model. This paper is most relevant to this research in the sense that both research papers use finite-population based models. However, the Talluri (2009) paper requires prior knowledge of sales rates for numerous pairs of time periods, which makes the implementation of the algorithm difficult to use in practice.

Our study fills the gap in the literature in that we propose a new estimation procedure which is free from demand distribution assumptions and does not require any extra knowledge of customer arrival rates. In addition, our approach includes parameters for customers for prices and product attributes that can serve as inputs for choice-based algorithms.

4.3 Model and Estimation

As discussed above, methods that rely on specific demand distribution assumptions are, on the one hand, unlikely to be accurate and verifiable; and on the other hand could generate inconsistent and biased estimation results. In this section, we propose a new estimation methodology that successfully overcomes the above drawbacks.

4.3.1 The Base Model

As in almost all existing choice-base revenue management models, we adopt a multinomial logit (MNL) model to capture customer choice behavior (Ben-Akiva and

Lerman, 1985). In MNL, a customer has different utilities over a set of available alternatives, and chooses the alternative providing the highest utility. Suppose that in time window t, a customer is faced with an available choice set S_t. Formally, let's define the utility of an alternative i within the choice set S_t [18] in time window t in the form

$$U_{it} = u_{it} + \varepsilon_{it}. \qquad (1)$$

The utility U_{it} has a deterministic component u_{it} and a random term ε_{it}. The random term is assumed to be an $i.i.d.$ Gumbel random variable. The deterministic component u_{it}, the mean utility, is a function of all observed attributes of an alternative i. Formally, $u_{it} = \beta^T X_{it}$

where X_{it} is a vector of k attributes of alternative i, and β is a k-dimensional vector of customer preferences over the set of attributes.

In most revenue management data sets, only observed purchases from the analyzed firm are recorded. The customers that decide to purchase a product from a competitor or not to purchase at all are unobserved. Following the existing literature, our model includes a no-purchase alternative to capture this missing data. Formally, the no-purchase utility is defined as

$$U_{0t} = u_{0t} + \varepsilon_{0t} \qquad (2)$$

[18] Here a choice set means all available products in a market when a customer starts a purchase inquiry. A customer might purchase one alternative among available products or would not make any purchase at all.

where u_{0t} is the mean no-purchase utility and ε_{0t} is also a Gumbel random variable. Since no-purchase has no measurable attributes, it is possible to assume $u_{0t}=0$. In MNL models, adding a constant to every utility value will not change choice probabilities (Ben-Akiva and Lerman, 1985). To facility our later modeling, we re-parameterize the mean no-purchase utility $u_{0t}=\gamma$.

Therefore, the choice probability of alternative i and the no-purchase probability for a customer arriving at time t are given by

$$P_{it}(\beta,\gamma)=\frac{\exp\left(\beta^T X_{it}\right)}{\sum_{j\in S_t}\exp\left(\beta^T X_{jt}\right)+\exp(\gamma)}, \quad i\in S_t \tag{3}$$

and $$P_{0t}(\beta,\gamma)=\frac{\exp(\gamma)}{\sum_{j\in S_t}\exp\left(\beta^T X_{jt}\right)+\exp(\gamma)}. \tag{4}$$

Accordingly, we can write the probability that a customer decides to make a purchase in time window t as

$$P_{1t}(\beta,\gamma)=1-P_{0t}(\beta,\gamma)=\frac{\sum_{j\in S_t}\exp\left(\beta^T X_{jt}\right)}{\sum_{j\in S_t}\exp\left(\beta^T X_{jt}\right)+\exp(\gamma)} \tag{5}$$

and conditional on a purchase being observed, the probability that a customer chooses alternative product i is

$$P_{it|1}(\beta)=\frac{\exp\left(\beta^T X_{it}\right)}{\sum_{j\in S_t}\exp\left(\beta^T X_{jt}\right)}. \tag{6}$$

Complete Data Likelihood

If all purchases and no-purchases are observed for the whole time period, we can write the full likelihood function. Let's define the observed number of purchases of alternative i in time window t as n_{it}, while n_{0t} is defined as the (unobserved) incidents of no-purchase. The complete data likelihood function can be written as

$$
\begin{aligned}
L(\beta,\gamma) = \prod_{t\in T}\left[P_{0t}^{\,n_{0t}}\prod_{i\in S_t}P_{it}^{\,n_{it}}\right] &= \prod_{t\in T}\left[P_{0t}^{\,n_{0t}}\prod_{i\in S_t}\left(P_{it|1}P_{1t}\right)^{n_{it}}\right] \\
&= \left[\prod_{t\in T}\left(P_{0t}^{\,n_{0t}}\prod_{i\in S_t}P_{1t}^{\,n_{it}}\right)\right]\left[\prod_{t\in T}\prod_{i\in S_t}P_{it|1}^{\,n_{it}}\right] \qquad (7) \\
&= \left[\prod_{t\in T}\left(P_{0t}^{\,n_{0t}}P_{1t}^{\,n_{1t}}\right)\right]\left[\prod_{t\in T}\prod_{i\in S_t}P_{it|1}^{\,n_{it}}\right],
\end{aligned}
$$

where T is the set of all time windows and $n_{1t} = \sum_{i\in S_t} n_{it}$ is the total number of observed purchases in time window t. When all purchase and no-purchase data are available, the maximum likelihood estimators of parameters β and γ can be found by maximizing the likelihood function, L.

Incomplete Data

However, as mentioned earlier, most revenue management data sets only contain the sales data for the firm itself, while purchase data from competitors are consistently unobserved. Therefore, with only observed customer purchases from the firm during a certain time period, we could not figure out whether only those customers arrived and made purchases, or more customers arrived but purchased from competitors or decided not to make a purchase.

Talluri and van Ryzin (2004) propose a finite-time estimation approach. In particular, they divide the complete time period into small slices so that there is at most one customer arrival in each slice. They further assume that in each time slice a customer will arrive with the probability (denoted by λ), while no arrival is defined with a probability $1-\lambda$. The approach essentially requires a Poisson-like demand assumption. The researchers then estimate a complete data likelihood, which includes both observed and unobserved customers, similar to that shown in Equation (7). Moreover, the authors use an Expectation-Maximization (EM) algorithm (Dempster et al., 1977) for the missing data problem. In particular, for each E-step, the algorithm finds an expected log likelihood function given a distribution of missing data. Then at each M-step, it maximizes the complete data log likelihood function. Iterations between the E-step and M-step finally converge to consistent estimates. A major drawback of this approach is that the way the authors divide the time period is quite arbitrary. Subsequent research (Newman et al., 2014; Talluri, 2009) notes that the discretization of time causes biases since the estimates depends on the length of a time slice. In general, implementing this method has caused both theoretical and practical concerns.

Two-Step Approach

Another way to tackle this MNL model with missing data is through the use of a two-step approach. McFadden (1978) points out that when choices of a subset of alternatives are unobserved, there are no consistent estimates for parameters exclusively linked to the utility of unobserved alternatives; that is, there is no consistent estimator for γ , the mean utility of no-purchasers in the complete data likelihood function. In addition, according to McFadden (1978), only using observations of choices in a subset of alternatives will suffice in finding consistent estimates for parameters , e.g., β in our MNL model, linked to the utility of observed alternatives.

Thus, as shown in the last line of Equation (7), total likelihood L can be decomposed into two partial likelihood functions, $L_1(\beta,\gamma)=\prod_{t\in T}\left(P_{0t}^{\;n_{0t}}P_{1t}^{\;n_{1t}}\right)$ and $L_2(\beta)=\prod_{t\in T}\prod_{i\in S_t}P_{it|1}^{\;n_{it}}$. Here the likelihood L_2 only depends on β . This likelihood of an MNL model is the likelihood concerning how customers choose any one of the alternatives, conditional on a purchase being observed. Further, the data in L_2 , X_{it} and n_{it} , are all observed. Therefore, as discussed above, according to McFadden (1978), the consistent estimators for β can be found by maximizing L_2. In addition, a nice feature of L_2 is that it is a globally concave and easy to find unique optimum.

From the last step, we can find the consistent estimators $\widehat{\beta}$ of β , and hold β constant at the value of $\widehat{\beta}$ in likelihood function L_1 . Then, we can retrieve estimates for γ by maximizing $L_1\left(\gamma\,|\,\widehat{\beta},\right)$. This type of two-step approach can help to avoid difficulties of directly maximizing the full likelihood L .

However, it is still problematic to maximize likelihood L_1 since all n_{0t} are missing data. As mentioned earlier, in most revenue management data sets, no-purchase customers are consistently unobserved. This implies that the market size in each time window is never observed. To solve this problem, Talluri (2009) proposes a heuristic by calculating the log risk-ratio between any two finite periods with the same customer arrival rate. By doing this, the author is able to remove market size from the estimation process. However, it is very complex to find pairwise periods with same arrival rate, considering that in almost all industry cases, customer arrival rates are unknown.

Newman et al. (2014) adopt an assumption of Poisson demand distributions. In their model, n_{0t} or market size, is modeled based on one more unknown parameters, λ , the average arrival rate of customers in each time window. Under their settings, the likelihood function of $L_1(\gamma,\lambda)$, however, will not be global concave. Newman et al. (2014) formulates likelihood L_1 as

$$L_1^{m_0}(\gamma,\lambda)=\prod_{t\in T}\frac{\left[\lambda P_{1t}\left(\widehat{\beta},r\right)\right]^{n_{1t}}}{\lambda P_{1t}\left(\widehat{\beta},r\right)}. \qquad (8)$$

However, it is very likely that the analysis will produce a local optimum rather than a global optimum. Therefore, parameter estimates may be unstable under certain conditions. In addition, as shown in section 4, if the true demand distribution in the real data set is far from the assumed Poisson distribution, parameter estimates will be unstable and biased. In section 4, we will use $L_1^{m_0}$ and L_2 to implement the estimation procedure in Newman et al. (2014) and compare their estimation performance with our models.

4.3.2 Adjusted Case-Control Sampling Method

Our estimation procedure is also a two-step approach. However, our methods are different from the existing methods described above in the second step for parameter estimations from the marginal likelihood function L_1 . Following Lancaster and Imbens (1996), we reformulate the model for L_1 to a case-control sampling model adjusted with unobserved data.

Given a consistent estimator $\widehat{\beta}$ from maximizing the likelihood L_2, we can rewrite the probability that a customer decides to make a purchase given the choice set S_t as

$$
\begin{aligned}
P_{1t}(\gamma) &= \frac{\sum_{j \in S_t} \exp\left(\widehat{\beta}^T X_{jt}\right)}{\sum_{j \in S_t} \exp\left(\widehat{\beta}^T X_{jt}\right) + \exp(\gamma)} \\
&= \frac{\exp\left(\widehat{w_t}\right)}{\exp(\gamma) + \exp\left(\widehat{w_t}\right)} \qquad\qquad (9) \\
&= \frac{\exp\left(\widehat{w_t} - \gamma\right)}{1 + \exp\left(\widehat{w_t} - \gamma\right)}
\end{aligned}
$$

where $\widehat{w_t} = \log\left(\sum_{j \in S_t} \exp\left(\widehat{\beta}^T X_{jt}\right)\right)$ can be taken as a constant for each choice set S_t.

Note that the available choice set for customers in each time window t is assumed fixed, following previous research (Talluri and van Ryzin, 2004). (Assuming available product alternatives vary in each time period t complicates the estimation procedure.)

Let us define a binary random variable y . If a customer makes a purchase from the firm, then $y=1$. Otherwise, $y=0$. Assume that in the population the covariates w have unknown discrete distribution $F(w)$ with unknown probability on a known set of points of support, $\{\widehat{w_t}\}$. Conditional on covariates w in the population, the probability of a customer deciding to make a purchase is given by $P(y=1|w)=P_{1t}(w;\gamma)$. Formally, we can write the logit of this probability as

$$\text{logit}\, P(y=1|w)=\phi(w)=w-\gamma. \qquad (10)$$

In studies when all purchases and no-purchases are known for a random sample of covariates, all the unknowns in the model are set as the linear parameter γ. It would be straightforward to estimate these models using established methods. However, in revenue management data sets, we only generally know observed purchases, not the no-purchases. Following the sampling scheme in Lancaster and Imbens (1996), observed purchases, the first sample data, can be thought of as independent random samples drawn from the subset of the population that make purchases (all samples with $y=1$) with the covariates observed. We then draw a second independent random sample, "pseudo-no-purchase", from the whole population with only the covariates observed. Note that it is naïve to assume that the second random sample consists of only no-purchase incidents ($y=0$), because both purchases ($y=1$) and no-purchases ($y=0$) are mixed in this dataset due to random sampling. We denote the observed purchases dataset as $z=1$ and the second sample dataset drawn from the whole population as $z=0$. It can be remarked that $z=1$ implies that $y=1$, while $z=0$ implies that we do not know whether $y=0$ or $y=1$.

Note that, in our model, the "pseudo-no-purchase" data are generated by $F(w)$, which is unknown to us. We should draw a sufficiently large sample size of "pseudo-no-purchase" test data through a uniformly random drawing over covariates in the population. In practice, as shown in section 4, to ensure the randomness in the "pseudo-no-purchase" dataset, we keep at least 1000 resampling data points with the same sample size of the test data.

We want to estimate $P(y=1|w)$. However, the observed purchase and "pseudo-no-purchase" data are generated by $F(w|z=1)$ and $F(w)=F(w|z=0)$ respectively. We need to adjust our model by following a case-control adjustment approach (McCullagh and Nelder, 1989). Let us denote D as a binary indicator ($D=1$ indicates that an observation is included in our data sample). Let $\rho_1=P(D=1|y=1)$ be the sampling rates of true purchases in our data. And let $\rho_0=P(D=1|y=0)$ be sampling rates of true no-purchases in our data. We assume that given y the sampling mechanism is independent from the covariate w.

The above discussion implies, $P(D=1|y=1,w)=P(D=1|y=1)$. By applying a Bayes rule, we can write

$$P(y=1\mid D=1,w)=\frac{P(D=1\mid y=1,w)P(y=1\mid w)}{P(D=1\mid y=0,w)P(y=0\mid w)+P(D=1\mid y=1,w)P(y=1\mid w)}$$
$$=\frac{\rho_1 e^{\phi(w)}}{\rho_0+\rho_1 e^{\phi(w)}} \tag{11}$$
$$=\frac{e^{\phi_c(w)}}{1+e^{\phi_c(w)}}$$

where logit $\phi_c(w)=\phi(w)+\log\frac{\rho_1}{\rho_0}$. Thus, the logistic model needs to be adjusted according to $\phi_c(w)$ due to our sampling mechanism.

We further need to find $\frac{\rho_1}{\rho_0}$. Let's denote $n_p=\sum_{t\in T} n_{1t}$ as the number of observed purchases ($z=1$), and n_u as the number of pseudo-no-purchases ($z=0$). Let N be the total population size. We denote by q the marginal probability for customers to make purchases in the population, and $q=P(y=1)$. Let n_{1u} and n_{0u} be the number of purchases and number of no-purchases respectively in the pseudo-no-purchase sample data. The number of true purchases in the population is qN. The number of purchases in our sample data is n_p+n_{1u}. Thus, we can get

$$\rho_1=P(D=1\mid y=1)=\frac{n_p+n_{1u}}{qN}. \tag{12}$$

The number of true no-purchases in the population is $(1-q)N$. The number of no-purchases in our sample data is n_{0u}. Thus we can also get

$$\rho_0=P(D=1\mid y=0)=\frac{n_{0u}}{(1-q)N}. \tag{13}$$

Therefore, the ratio $\frac{\rho_1}{\rho_0} = \frac{n_p + n_{1u}}{n_{0u}} \frac{1-q}{q}$. Note that n_{1u} and q are both unknown. Ward et al. (2009) consider two scenarios: (1) when the marginal probability q is given. Ward et al. (2009) take an approximation by replacing n_{1u} and n_{0u} by the expected number of purchases and no-purchases in the pseudo-no-purchase sample data; (2) when q is not given and identifiable, the authors also discuss joint estimation of q and the regression function. In revenue management problems, market share data are generally not exogenously given. As opposed to Ward et al. (2009), we use the fraction of true purchases in the pseudo-no-purchase sample data to approximate q . That is,

$$\frac{\rho_1}{\rho_0} \approx \frac{n_p + n_{1u}}{n_{0u}} \frac{1 - \frac{n_{1u}}{n_u}}{\frac{n_{1u}}{n_u}} = \frac{n_p + n_{1u}}{n_{1u}}. \tag{14}$$

where $n_{1u} = \sum_{i \in A} y_i$ and A is the index set of pseudo-no-purchase data. Therefore, we get

$$P\left(y = 1 \mid D = 1, w\right) \approx \frac{\frac{n_p + n_{1u}}{n_{1u}} e^{\phi(w)}}{1 + \frac{n_p + n_{1u}}{n_{1u}} e^{\phi(w)}}, \tag{15}$$

or equivalently the logit is $\phi_c\left(w\right) = \phi\left(w\right) + \log \frac{n_p + n_{1u}}{n_{1u}}$.

Finally, we can write the likelihood for our sample data considering both observed purchase z and true purchase y as

$$
\begin{aligned}
L_1^{m_1}(\gamma \mid z, y, w) &= \prod_i P(y_i, z_i \mid D_i = 1, w_i) \\
&= \prod_i P(y_i \mid D_i = 1, w_i) P(z_i \mid y_i, D_i = 1, w_i). \qquad (16)
\end{aligned}
$$

We know that $P(z_i = 1 \mid y_i = 1, D_i = 1, w_i) = \dfrac{n_p}{n_p + n_{1u}}$ and

hence $P(z_i = 0 \mid y_i = 1, D_i = 1, w_i) = \dfrac{n_{1u}}{n_p + n_{1u}}$. Further, $P(z_i = 0 \mid y_i = 0, D_i = 1, w_i) = 1$,

in that there are no true no-purchases $y = 0$ in the observed purchase sample data. Because none of these sampling probabilities depends on γ, they can be taken as constant in the likelihood function. Therefore, we can further write

$$
\begin{aligned}
L_1^{m_1}(\gamma \mid z, y, w) &\propto \prod_i P(y_i \mid D_i = 1, w_i) \qquad (17) \\
&= \prod_i \left(\frac{e^{\phi_c}}{1 + e^{\phi_c}} \right)^{y_i} \left(\frac{1}{1 + e^{\phi_c}} \right)^{1 - y_i}.
\end{aligned}
$$

All the unknowns of the model are the parameter γ and true purchases in the pseudo-no-purchase sample data. Hence this likelihood function $L_1^{m_1}$ can be formalized as a missing data problem.

4.3.3 The Expectation-Maximization Algorithm

The likelihood function $L_1^{m_1}(\gamma \mid z, y, w)$ can be maximized using the Expectation-Maximization (EM) algorithm (Dempster et al., 1977). Since the true y observations in the pseudo-no-purchase sample dataset are unknown, we can take these y observations as missing data. The EM algorithm solves the missing data problems by iterating between the expectation and maximization steps. We try to impute the unknown y at each iteration and fit a model using this imputed y. We adopt a similar EM algorithm as Ward et al. (2009). The difference is that we jointly estimate marginal probability with parameters, as discussed earlier. Therefore, our approach does not need extra exogenous knowledge of market share, which is normally not available in real revenue management data.

During each iteration we go through the following steps, until subsequent iterations result in a stable model:

Step 1: Randomly draw a large sample size of pseudo-no-purchase data.

Step 2: Choose the starting value: $\hat{y}_i^{(0)}$ for $z_i = 0$.

Step 3: Repeat until convergence:

- Maximization step:
  - Calculate $\hat{\phi}_c^{(k)}$ (and $\hat{\gamma}^{(k)}$ consequently) by fitting a linear logistic model, L_1^m, of $\hat{y}^{(k-1)}$ given w.
  - Update $\widehat{n_{1u}}^{(k)} = \sum_{i \in A} \hat{y}_i^{(k-1)}$
  - Calculate $\hat{\phi}^{(k)} = \hat{\phi}_c^{(k)} - \log\left(\dfrac{n_p + \widehat{n_{1u}}^{(k)}}{\widehat{n_{1u}}^{(k)}}\right)$
- Expectation step:

○ $\widehat{y}_i^{(k)} = \dfrac{e^{\hat{\phi}^{(k)}}}{1+e^{\hat{\phi}^{(k)}}}$ for $z_i = 0$ and $\widehat{y}_i^{(k)} = 1$ for $z_i = 1$

The pseudo-no-purchase samples should be drawn randomly each time before the EM iterations. To ensure the randomness requirement due to our case-control adjustment methods, we choose to uniformly random draw a large enough sample size with respect to all observed covariates.

The initial estimate of y for $z = 0$ could be set as our best guess of marginal probability of true purchases in the population, $q = P(y = 1)$. In practice, if we have any prior knowledge of the aggregate market share during the time windows, it works as a starting value to get expectations of $y_i = q$. Even when it is impossible to retrieve such prior information, we can always make a guess to set $y_i = 0.5$. At each Maximization iteration, the algorithm only needs to fit a linear logistic model, which ensures consistent estimation results. In practice, to make sure the EM algorithm convergences, we need to set a very tight tolerance, normally less than 10^{-9}.

As we mentioned earlier, to jointly estimate choice parameters and market size is challenging without actual observations of no-purchase customers. In our EM algorithms, we handle the missing data q by replacing q with an approximation, $\dfrac{\sum_{i \in A} \hat{y}_i}{n_u}$, from the last expectation step. However, in practice we need to be very cautious since identifiability issues emerge. Ward et al. (2009) point out that q is identifiable only if the regression function $\phi(w)$ has a special structure; e.g., linear logistic regression as in our research. Even when q is identifiable, the estimates are highly variable, because q and γ are highly correlated. Therefore, it is safer to retrieve any exogenous information about q and apply sensitivity analysis on the results.

Finally, we summarize our two-step estimation procedure as follows:

- The first step is to find consistent estimators $\widehat{\beta}$ by maximizing the likelihood function $L_2(\beta)$.
- Given $\widehat{\beta}$ as constant in the likelihood function, $L_1^{m_1}(\gamma \mid z, y, w)$, the second step is to find a consistent estimate of γ from $L_1^{m_1}(\gamma \mid z, y, w)$ by using the EM algorithm.

Note that one drawback that our algorithm shares with any two-step approach is that the inverse Hessian matrix of the functions that are calculated cannot be used alone to calculate the standard error of the estimators. We can adopt a bootstrapping (Efron and Tibshirani, 1993) approach among proposed methods in the literature. The bootstrapping is simple and straightforward to use to calculate standard errors for our estimate results.

4.4 Simulation Tests

Our approach has the main advantage over existing methods as it allows for an arbitrary demand distribution and requires no prior knowledge about customer arrival rates, while still providing consistent parameters estimates. The implementation of our method facilitates researchers and practitioners to estimate parameters in real choice-based revenue management systems without requiring extra information on the arriving demand pattern. To understand the magnitude of these benefits, we focus on a comparison with Newman et al. (2014); that is because: (1) they use a 2-step approach which is similar to ours; (2) their approach is one of the few approaches which can estimate customer preferences over prices and other product attributes; and (3) they solve the drawback of arbitrary discrete time slices in Talluri and van Ryzin (2004). In addition, Newman et al. (2014) report an improvement over Talluri and van Ryzin (2004) in both computational efficiency and estimation accuracy.

Specifically we are interested in the following questions:

- Which approach performs better in terms of uncovering the unobserved market and in estimating choice parameters under various industry applications?
- What is the performance of Newman et al. (2104) when the real demand is different from its assumed demand distribution?

We use simulation data modeled after an actual industry data set to compare the two approaches. We believe simulated data, rather than actual booking data, works best for this test. First, with simulated data, we know the underlying true model parameters, while we have no access to a revenue management data set with market size or customer choice preference information. Second, a controlled simulation experiments allow us to evaluate and compare the performance of different methods under various market settings. Therefore, simulation tests have been widely adopted in existing research in this area to test algorithms.

Our simulation data are generated based on a single urban hotel, “Hotel 4”, in a publicly available dataset from Bodea et al. (2009). As a property of a major hotel chain, Hotel 4 targets medium-income-level customers and has total of seventy rooms. This hotel offers up to nine different room types (e.g., king non-smoking room and queen smoking room) for booking at most times. The data were collected with five-week check-in dates, and with a minimum booking horizon of four weeks. Rate and room type availability at the time of booking and customers’ final bookings are recorded. In total, the data contains 288 bookings.

Real customer parameters and product attributes are directly extracted from the data set. We define each “booking-check-in” as a time window during which the hotel offers relatively fixed combinations of different room types and prices. This implies that customers booking a room on the same day for the same check-in date are faced with a relatively fixed choice set of products. In the original data set, we only observe customers that made purchases, their choices of products and the attributes of these products in each time window.

As discussed in section 3.1, based on the observed purchases, we can find consistent estimates of customer preferences over prices and other product attributes. Both the model (m_0) proposed by Newman et al. (2014) and our model (m_1) share the same step 1 by maximizing likelihood function L_2, with which it is easy to find the global optimum. Our objective is then to compare the performance of the model m_0 and our model m_1 in how well they uncover the unobserved market.

Therefore, we focus on step 2 and set $\widehat{\beta}$ as constant in our simulated data for step 2. The consistent estimates $\widehat{\beta}$ from the real hotel data are shown in Table 4.1.

Table 4.1 Consistent Estimators from Step 1

Parameter	$\widehat{\beta}$	Parameter	$\widehat{\beta}$
β_{Queen1}	0	β_{King3}	-2.855
β_{Queen2}	-1.392	β_{Standard}	-3.493
β_{Queen3}	-4.433	β_{Suite1}	-0.7203
β_{King1}	0.4161	β_{Suite2}	0.5855
β_{King2}	-2.535	β_{Price}	-0.1019

There are in total nine room types. The first type, β_{Queen1} is set at zero. The price elasticity is assumed to be equal across all time windows. In practice, to estimate customer preferences over the firm's products in step 1, we can consider more flexible specifications of the model. For instance, (1) customers may have heterogeneous preferences over the same room type and price; and (2) customers who have made purchases are generally more price sensitive. However, in this simulation test, we only need to evaluate the performance of models in step 2. It will not affect our results to keep a parsimonious model structure in step 1. We will use consistent estimators $\widehat{\beta}$ in Table 4.1 to calculate $\widehat{w_t}$ as true values of covariates in the simulation.

We also consider two scenarios of demand distributions in the simulation:

1. Poisson distribution with the customer arrival rate at $\lambda = 60$ per day. As we mentioned in section 2, this Poisson assumption restricts demand variability in models, but previous researchers have overlooked this in order to keep their models tractable. In scenario 1, the Poisson demand distribution has a coefficient of variation of $\frac{\sigma}{\mu} = \frac{\sqrt{60}}{60} \approx 0.13$, which is significantly lower than a c.v. of 2 or 3 in the real revenue management data set.
2. Lognormal distribution with mean and standard deviation on the log scale, $v = \log(40)$ and $\tau = 1$ respectively. We assume that the number of customer arrivals in each time window follows the lognormal distribution and the numbers are rounded to integers. In scenario 2, the average number of customer arrivals is approximately 62 per day. In our synthetic data, the coefficient of variation of observed purchases is about 2.7, which is at the same level found in the real revenue management data set.

Therefore, scenario 1 works as a naïve assumption as in model m_0, while scenario 2 can be taken as a more realistic demand benchmark. We will compare the performance of the modes m_0 and m_1 under both scenarios and aim to answer the above questions.

Finally, for both scenarios, we set $\gamma = -6$ and the hotel's market share at approximately 7%, which is in the same order of magnitude as the actual market share of the hotel(Bodea et al., 2009). By using these parameters, we generate two sets of simulated data containing one year's check-in days with 4-week booking curves. In the real hotel dataset, there are a total of 288 available product set combinations of different room types and their prices in different time window. We take these real product sets as given and randomly assign them into our 10,192 booking-check-in time windows as available choice sets for arriving customers. In each simulation run, there are 60,000 observed purchases.

We generate the simulation data and perform the subsequent estimation of model parameters by using R v3.2.2.

4.4.1 Performance Comparison

The estimation results for the two models using simulation data are listed in Table 4.2. All the estimates are significant at the 1% level due to the large size of our simulated data. The final log likelihood results are reported for both models, but note that they are not directly comparable to each other. This is because (1) the underlying structures of the two models are different; and (2) in model 1, as discussed in section 3.2, we need to draw a large size (at least 10 times the number of observed purchases) of pseudo-no-purchase samples. In both scenarios, each model is run 50 different times with 50 different starting values. After the models converge, the model with the highest log likelihood value is used to estimate parameters.

Both models only need to estimate one parameter γ (no-purchase constant) at this stage. From Table 4.2, we note that model m_0 works well only when the assumed Poisson distribution is true (Scenario 1). The deviation from the true value (absolute error) is less than 5%. In Scenario 2, however, when the true demand has a reasonably large variability as in many real revenue management data sets, the deviation from the true value jumps to over 16%. The underlying reason is due to the inappropriate demand assumption. Our task is to jointly estimate choice probabilities and market size, which are highly correlated. Inappropriate specification of the demand distribution introduces bias into the estimation of the no-purchase constant γ. In general, we find that it is not valid to adopt Poisson demand distribution assumptions as most existing research does in this area to enjoy the benefit of tractability of models. Any wrong specification of demand distributions will cause unstable and biased estimates. Therefore, we urge both researchers and practitioners to verify their demand distributions and perform sensitivity analysis when implementing distribution dependent methods to similar problems like ours.

Table 4.2 Estimation Performance of the Two Models

			Model m_0		Model m_1	
	Parameters	True values	Estimate (Std. Error)	Deviation from the true (%)	Estimate (Std. Error)	Deviation from the true (%)
Scenario 1	γ	-6.0	-5.747 (0.183)	4.2	-6.033 (0.014)	0.5
	Log likelihood	-549.018			-8320.5	
Scenario 2	γ	-6.0	-5.031 (0.218)	16.2	-6.043 (0.015)	0.7
	Log likelihood	-1075.172			-8389.5	

On the contrary, our model performs consistently well, with both errors within 1% in both scenarios and dominates the estimation accuracy of Newman et al. (2014). It is well expected since our method is independent of any demand distribution assumptions. Meanwhile, no other exogenous knowledge about market share is required.

4.4.2 Empirical Unbiasedness and Robustness

The above results are dependent on our simulated data. To further evaluate both methods and perform robustness checks, we generate 25 distinct synthetic data sets based on a similar generating rule. We only focus on the realistic demand setting as in scenario 2 to further explore how well both models work. We then apply both methods to the 25 synthetic data sets. The results for model m_0 and our model m_1 are summarized and plotted in Figures 4.1 and 4.2 respectively.

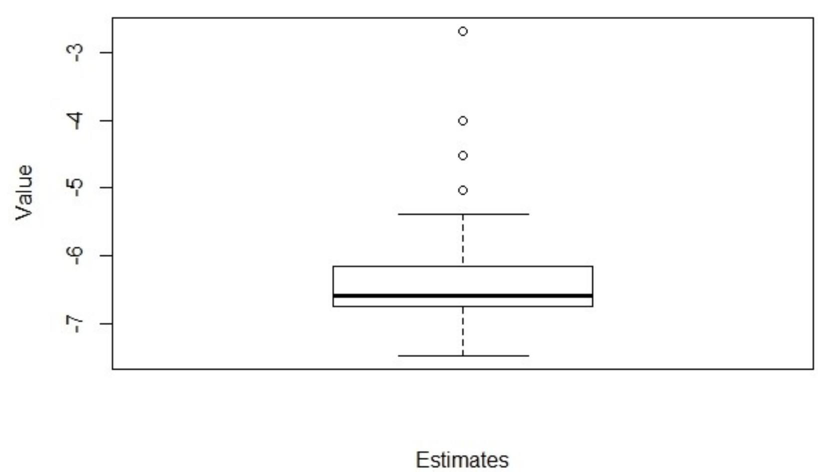

Figure 4.1 Boxplot for 25 Test Results of γ in m_0

From Figure 4.1, we note that when demand variability is reasonably high as in these tests, the performance of model m_0 turns out to be very unstable across different data sets. The variability among the 25 estimates is quite high. The median (that is the thick band inside the box in Figure 4.1) is around -6.5. The first and third quartiles (the top and bottom of the box) are within the range between -6 and -7, which is not too far from the true value of γ (-6.0). There are, however, at least 4 outliers (big dots outside of the box) located far above the end of the box, with one having an error of over 50%. This finding echoes our thoughts that those methods contingent on assumed demand distributions easily cause unreliable and even biased estimates.

Figure 4.2 shows that our estimation performance is independent of any simulated data and our results, on average, are very close to the true value. The median of these estimation results is around -6.05.

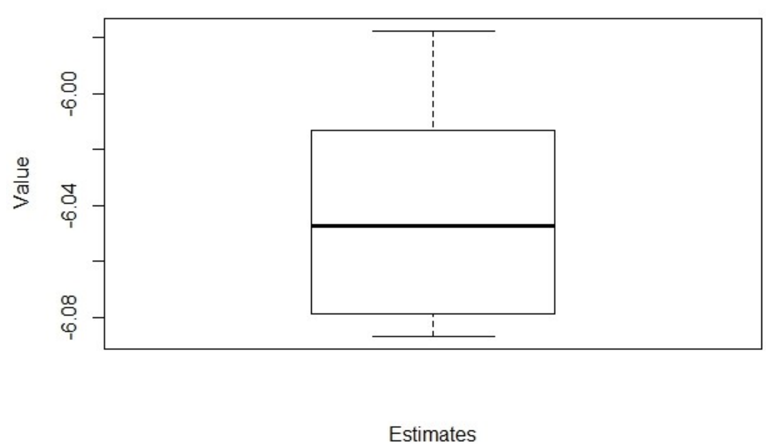

Figure 4.2. Boxplot for 25 Test Results of γ in m_1

4.5 Implementation in Revenue Management

The implementation of choice-based revenue management systems requires the estimation of customer choice parameters as inputs. However, in a majority of the existing research, where no-purchase customers are never observed, exclude parameters on price and other product attributes. This makes it almost impossible to explore the fundamental questions: What is a customer's willingness to pay? And how will the willingness to pay affect a firm's prices and assortment decisions? Our proposed method can fill the gap to capture customer preferences on product- related attributes. In addition, compared with existing estimation procedures considering prices, our models allows for arbitrary demand distributions and requires no extra demand information.

We generate a simulated dataset based on the real hotel data as discussed in section 4 to demonstrate how to implement our estimation procedures with real revenue management systems. The simulated dataset contains 288 time windows, in each of which a set of products are available. We take the displayed product sets directly from the real data with real price and room types. All true values are set as in scenario 2 as described in section 4.

Given the synthetic data with only observed purchase data, we can estimate choice parameters using our models. For any unique displayed product set in each time window, we can calculate the probability a customer will buy any product and the total expected revenues that will accordingly earn.

Here is an example. In a time window, there are 9 rooms available in total and prices p_i ($i = 1,...,9$) are known. With our estimates of γ , we can calculate the probability that a customer will choose each room i, as discussed in section 2, as $\Pr_i$. Thus the expected revenue of this displayed product set is $R_t = \sum_{i=1,\dots,9} \Pr_i p_i$. We can also calculate the probability of the customer buying from the firm as $\Pr^t_{buy} = \sum_{i=1,\dots,9} \Pr_i$. We plot all portfolios ($R_t, \Pr^t_{buy}$) and can easily identify an efficient frontier (EF) among all possible offerings. In Figure 4.3, we plot the EF from our models and the one based on the true parameters.

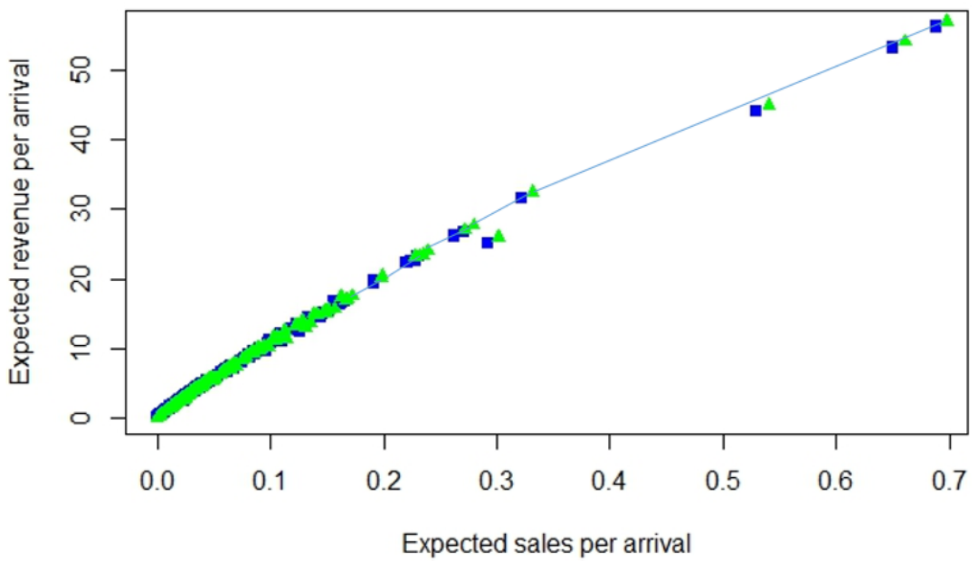

Figure 4.3 Efficient Frontier for True Value and Our Model

The efficient frontier is determined by connecting points on the outline of all possible points; all points beneath the outline are dominated by efficient frontier. The efficient frontier should be considered as possible inputs by a revenue management dynamic programming (Talluri and van Ryzin, 2004). As shown in Figure 4.3, based on the efficient frontier (depicted in green triangles connected by the line) our estimation results closely mirror the frontier with true parameters (depicted in blue squares). Therefore, estimates given by our models can serve as good inputs for revenue management systems.

We also plot the efficient frontier based on estimates of model m_0 (red squares connected by lines) and compare it with ours (green triangular connected by lines), as shown in Figure 4.4. The EF determined by m_0 significantly deviates from our EF. Therefore, any biased estimates, as with m_0, will produce an incorrect EF and consequently will provide wrong inputs for revenue management optimization algorithms.

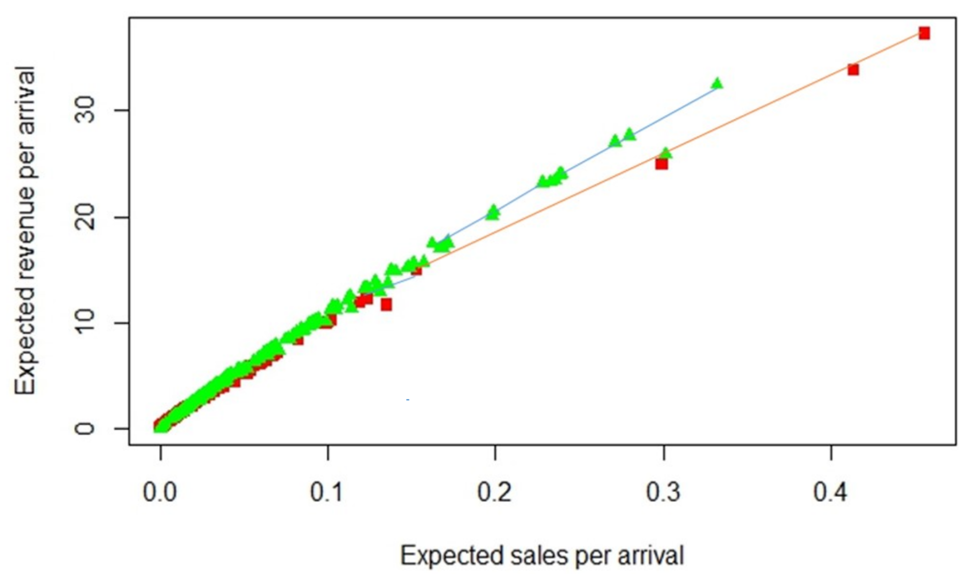

Figure 4.4 Efficient Frontier for Model m_0 and Our Model

Finally, we use the algorithm in Vulcano et al. (2012) to perform estimations. As mentioned earlier, this estimation algorithm (m_2) is different from both the model m_0 and our model, since it is not able to estimate price coefficients. In addition, it also depends on a strict assumption of Poisson demand. We plot the efficient frontier based on the estimates of m_2 (blue dots connected by lines) and compare it with ours (red squares connected by lines), as shown in Figure 4.5.

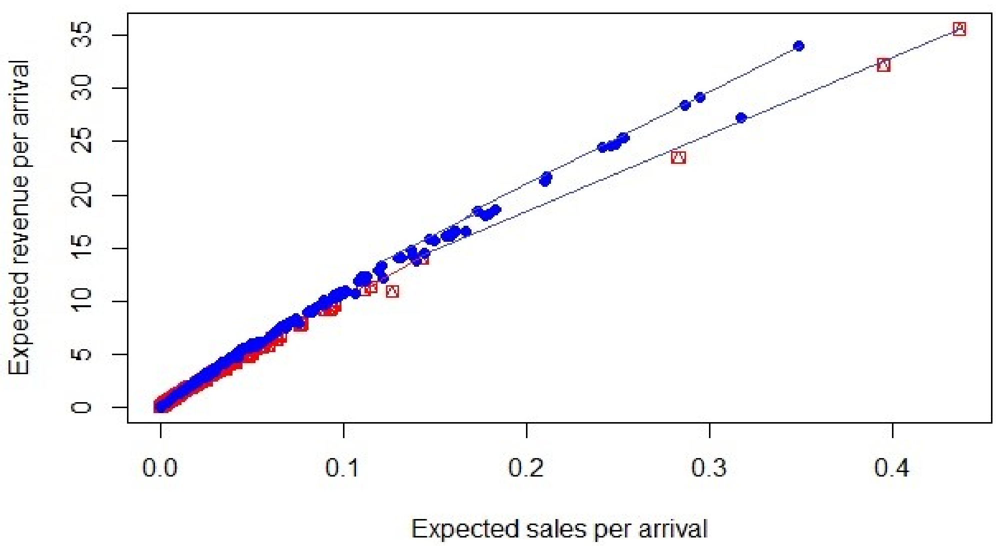

Figure 4.5 Efficient Frontier for Model m_2 and Our Model

The EF determined by m_2 significantly deviates from our EF Model m_2 suffers from the same problem as m_1, since the estimates will be biased when the true demand distribution is far from the Poisson distribution. Moreover, m_2 cannot estimate price coefficients and, therefore, cannot provide price adjustment as inputs for revenue management systems.

In general, compared with other methods, our estimation quality is consistently superior. The advantage of our model is more prominent, especially when true demand has large variability and is far from a strictly assumed Poisson distribution.

4.6 Conclusions

Choice-based revenue management has been an active research area in recent years. Compared with traditional product-based revenue management, it incorporates customer behavior into revenue management algorithms. Both theoretical and empirical research have reported potential benefits to implement choice-based revenue management systems (e.g., Talluri and van Ryzin, 2004; Vulcano et al., 2010). Moreover, revenue management managers have long complained that existing revenue management software systems (i.e., product-base systems) fail to capture customers' willingness to pay (Weatherford 2009). However, in practice, there is no large-scale implementation of choice-based systems. This may be due to the following reasons. First, choice-based systems require information about products available to customers at the time of booking. Collecting and validating product availability from existing revenue management systems are technically challenging and time-consuming tasks. (Bodea et al, 2009). Secondly, choice-based systems are fundamentally different from existing product-based systems. Therefore, to successfully implement choice-based systems, firms need to make significant investments in developing revenue management algorithms and customer support systems.

This study investigates how to estimate customer preferences that serve as inputs for choice-based revenue management systems. To estimate parameters in choice-based revenue management systems has been recognized as challenging because normally the firm only have their own observed purchases, while those customers who purchase from competitors or do not make purchases are unobserved. Many existing methods which try to solve this problem rely on assumptions of demand distributions, e.g., Poisson distribution. However, we point out two main drawbacks for this group of methods: (1) widely adopted Poisson demand distributions have much lower variability than those in real revenue management datasets; (2) and, more importantly, since a significant part of the market is consistently unobserved, assumptions on market demand are both unlikely to be true and unverified. Our simulation tests demonstrate that any naïve specification of demand distributions could generate unreliable and biased estimates, e.g., parameter estimation errors as high as 16%.

We propose a new estimation method, which is essentially a finite-population approach but with missing data. Our method is based on a case-control sampling approach as in Lancaster and Imbens (1996), which estimate choice models with only purchases observed. To make the estimation feasible, we adopt the Expectation-Maximization (EM) algorithm (Dempster et al., 1977) for this missing data problem. Our method does not require any prior knowledge of the customer arrival process and allows for an arbitrary demand distribution. Therefore, our estimation procedure can be implemented in many realistic industry cases. Compared to previous methods, our model performs superior when the true demand is highly variable and is far from the assumed Poisson distribution.

While our results are very promising, considerable more research is needed in the future. First, our estimation procedure is a type of two-step approach, which can provide theoretically consistent estimates, but has lower efficiency (i.e., larger standard error). A possible way is to use case-control approach without decomposition of the full likelihood. But as Ward et al. (2009) mentioned, the identification of marginal probability in the population emerges as an issue since the specification of a logistics model is no longer linear. A Bayesian approach with an informative prior for marginal probability can be used when there is no precise information on marginal probability. We will leave this to future research.

Second, in the case-control approach, the marginal probability is identifiable but highly correlated with the no-purchase constant. It is safer to collect exogenous information on marginal probability (i.e., market share) and perform sensitivity analysis. In practice, managers might have expertise to guess the aggregate level market share or collect information through third-party channels. If this type of information is available, it is easy to validate and improve the performance of our method.

Finally, in this study, we assume that all customers are homogenous in purchase behavior. But in reality, customers are heterogeneous with respect to same product attributes. For example, van Ryzin and Vulcano (2015) find that considering customer heterogeneity in estimation could significantly improve estimation power. It is straightforward to include random coefficient parameters of β in our first-stage estimation to capture the heterogeneity among customers. However, in our second stage, to capture heterogeneity of the no-purchase constant γ will result in issues related to identification. We will leave this work to future research.

Chapter 5: Conclusions and Future Research

The core of service operations management is to help firms deploy their operations and deliver services effectively to the right customers at the right time. Thus, understanding customer incentives and decision processes can benefit firms' decision-making. This dissertation investigates service outsourcing and revenue management in the service industry (i.e., airline and hotel industries) while considering customer behavior.

5.1 Service Outsourcing

The answer to the question "what are the outcomes of outsourcing" remains unclear, given endogeneity issues embedded in firms' profit-maximizing decision-making. In the first two essays of this dissertation, we aim to answer this question under a specific context: network airlines' outsourcing to independent regional airlines in the U.S. airline industry.

Essay 1 examines the impact of outsourcing on a firm's demand by exploring customer preferences over different products. Then Essay 2 extends the research to model both the demand and supply sides. On the demand side, a random coefficient logit model is employed to investigate unobserved customer heterogeneity. On the supply side, a game theoretic model is used to capture the market structure and firms' strategic interactions. This is the first structural model, of which we are aware, to empirically evaluate outsourcing outcomes. The counterfactual analysis can be used to evaluate many impacts, such as impacts on prices, market shares and profits, before employing an outsourcing.

While our results are promising, considerably more research could be implemented in the future. First, our demand model accounts for customer heterogeneity only for price sensitivity due to data limitations. If more customer-level data are available, e.g., individual demographical data, we could explore different tastes in both price and product attributes across customers.

Secondly, we have modeled a supply-side game by assuming that there exists only horizontal interactions among firms, since the transaction fees between outsourcers and service providers are inaccessible. A full game considering both horizontal interactions and vertical interactions would provide further insights into firm behavior and decisions. We will leave this to future research.

5.2 Revenue Management

Estimating the parameters in choice-based revenue management systems has been recognized as challenging because normally firms only have data on their own observed purchases, while customers who purchase from competitors or do not make purchases are unobserved. Many existing methods attempt to solve this problem by relying on assumptions of demand distributions, e.g., Poisson distribution.

We propose a new estimation method, which does not require any prior knowledge of the customer arrival process and allows for an arbitrary demand distribution. Therefore, our estimation procedure can be implemented in many realistic industry cases.

Our approach can be extended into three directions. First, our estimation procedure is a type of two-step approach, which can provide theoretically consistent estimates, but has lower efficiency (i.e., larger standard error). A possible way is to use case-control approach without decomposition of the full likelihood. But as Ward et al. (2009) mentioned, the identification of marginal probability in the population emerges as an issue since the specification of a logistics model is no longer linear. A Bayesian approach with an informative prior for marginal probability can be used when there is no precise information on marginal probability. We will leave this to future research.

Second, in the case-control approach, the marginal probability is identifiable but highly correlated with the no-purchase constant. It is safer to collect exogenous information on marginal probability (i.e., market share) and perform sensitivity analysis. In practice, managers might have expertise to guess the aggregate level market share or collect information through third-party channels. If this type of information is available, it is easy to validate and improve the performance of our method.

Finally, we assume that all customers are homogenous in their purchase behavior. But in reality, customers are heterogeneous with respect to some product attributes. van Ryzin and Vulcano (2015) find that considering customer heterogeneity in the estimation procedure can significantly improve the estimation power. It is straightforward to include random coefficient parameters of β in our first-stage estimation to capture the heterogeneity among customers. However, in our second stage, to capture heterogeneity of the no-purchase constant γ will result in issues related to identification. We will leave this work to future research.

Appendices

Sample R Codes: Estimating Choice Models with Censored Sales Data in Revenue Management

A1. Simulated Data Generation

```
library(msm)
gamma_f<-rep(0,25)
for(ss in 1:50) {
t<-360*28
 lambda<- 40
 #lambda_add<- rep(lambda,t)
 a1<- rep(1,t)
 NT<-lambda*t

#Set different arrival process
 set.seed(ss)
 #arrival<- rpois(t,lambda)
 #arrival<- as.integer(NT*rdirichlet(1,a1)+rtnorm(t, mean=1, sd=1, lower=1,
     upper=Inf))
 #arrival<-as.integer(rtnorm(t, mean=lambda, sd=3*lambda, lower=1, upper=Inf))
 arrival<- as.integer(rlnorm(t,meanlog=log(40),sdlog=1))
 cv.arrival<- sd(arrival)/mean(arrival)

 #NT<- 10000
 #xtotal<-rnorm(t,0,1)
 xtotal<- nita
 xtest<- cbind(1,xtotal)
```

```
b<-c(6,1)
p<-exp(xtest%*%b)
p<-p/(1+p)
#arrival<-Narrival/p
N1T<- sum(arrival)
lambda_avg<- N1T/t

arrivalC<- rep(0,(t+1))
arrivalC[1]<-1
y_init<- rep(0,N1T)
x_init<- rep(0,N1T)
arrival.t<- rep(0,t)
for(i in 1:t){
  arrivalC[i+1]<- arrivalC[i]+arrival[i]
  #set.seed(42)
  y_init[arrivalC[i]:(arrivalC[i+1]-1)]<-rbinom(arrival[i],1,p[i])
  arrival.t[i]<- sum(y_init[arrivalC[i]:(arrivalC[i+1]-1)])
  x_init[arrivalC[i]:(arrivalC[i+1]-1)]<-xtotal[i]}

cv.arrivalt<- sd(arrival.t)/mean(arrival.t)
xi<- sum(y_init)/N1T
#lambda_avg<- N1T/t
x1<- x_init[y_init==1]
#xtest1<-cbind(1,x1)
x0<- x_init[y_init==0]
np<- length(x1)
nu<- N1T
xpar<- c(x1, xsample)
#for bayesian
#xpar_temp<- c(x1,x0)
```

```
 #xpar2<- cbind(1,xpar)

 z1<- rep(1,np)
 z0<- rep(0,nu)
 z<- c(z1,z0)
 #for bayesian
 #z1_temp<- rep(1,np)
 #z0_temp<- rep(0,length(x0))
 #z_temp<- c(z1,z0)
 tolerance<- 0.000001
 #b1<-c(3,1)
 #xi1<-0.09
}
```

A2. Non-Linear Optimization for Model m0

```
 #Poisson distribution
 ll.logit<-function(a) {
   b<- c(a,1)
   p<- exp(xtest%*%b)
   p<- (p/(1+p))
   lambda.temp<- sum(arrival.t)/sum(p)

   lambda.test<- lambda.temp *p
   #lambda.test<- lambda_avg*p
   ll<- (-sum(dpois(arrival.t,lambda.test,log=T)))
   ll}
 a0<- 1
 out.bin1<-optim(a0,ll.logit,method='Brent',lower=-50,upper=50)

 out.bin2<-nlm(ll.logit,out.bin1$par,hessian=T)
```

```
cbind(out.bin2$estimate,sqrt(diag(solve(out.bin2$hessian))))

gamma_f[ss-41]<- out.bin2$estimate

b.fit<- c(out.bin2$estimate,1)
p.fit<- exp(xtest%*%b.fit)
p.fit<- (p.fit/(1+p.fit))
lambda.fit<- sum(arrival.t)/sum(p.fit)
```

A3. EM Algorithms to Fit Model m1

```
# Draw large size pseudo- no-purchase samples and keep 1000 samples
n.iter=1000
res=matrix(NA,n.iter,3)
for(i in 1:n.iter){
    nu<- N1T
    xsample<- sample(xtotal,nu,replace=T)
    xpar<- c(x1, xsample)
    z1<- rep(1,np)
    z0<- rep(0,nu)
    z<- c(z1,z0)
    tolerance<- 0.000000001

    empar=function(z,xpr,xi,nu,tol)
    {
        # Initial E-step
         yy=z
        yy[z==1]=1
        temp=rbinom(nu,1,xi)
        yy[z==0]=temp
        n1u=sum(yy[z==0])
```

```
  #y[z>0]=z[z>0]
  #y[z==0]=mean(z[z>0])

  # Initial M-step
  a=glm(yy~offset(Xpr*1),family="binomial")
  #a=glm(yy~Xpr,family="binomial")
  betaold=rep(0,length(beta))
  beta=a$coef
  wew=exp(eta)/(1+exp(eta)
 corrtr=-log(sum(z>0)+n1u)+log(n1u)
eta=a$linear+correction
  while(max(abs(beta-betaold))>tol)
  {
        # E-step
        we.temp=we[z==0]
        yy.temp1=rep(0,length(we.temp))
        for(i in 1:length(we.temp)){
              yy.temp1[i]=rbinom(1,1,we.temp[i])
        }
        yy[z==0]=yy.temp1
        n1u= sum(yy[z==0])

        # M-step
        a=glm(yy~offset(Xpr*1),family="binomial")
        #a=glm(yy~Xpr,family="binomial")
        betaold=beta
        beta=a$coef
        betasum=summary(a)
        cor=-log(sum(z>0)+n1u)+log(n1u)
        wta=a$linear+correction
```

```
        }
        n1u.avg=sum(we[z==0])
        phi.avg=n1u.avg/nu
        phi=n1u/nu
        list(beta=beta,betasum=betasum,phi=phi,phi.avg=phi.avg)
    }
    #empar(Ind,x_init,xi,tolerance)
     est=empar(z,xpar,0.05,nu,tolerance)
     #res=c(est$beta,est$betasum,est$phi,est$phi.avg)
     res[i,]=c(est$beta,est$phi,est$phi.avg)
}
```

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